To the Graduate Council:

I am submitting herewith a thesis written by Marie A. Colson entitled "Landscape Patterns and Patch Dynamics in Hamilton County Tennessee over a Forty Year Period: Applicability to the Conservation of the Eastern Box Turtle." I have examined the electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Environmental Science.

Thomas P. Wilson, Ph.D., Major Professor

We have read this thesis
And recommend its acceptance:

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Accepted for the Council:

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Interim Dean of the Graduate School

(Original signatures are on file with official student records.)

LANDSCAPE PATTERNS AND PATCH DYNAMICS IN HAMILTON COUNTY OVER A FORTY YEAR PERIOD: APPLICABILITY TO THE CONSERVATION OF THE EASTERN BOX TURTLE

A Thesis

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DEDICATION

This thesis is dedicated to the memory of Beverly, Pardee and Thomas

ABSTRACT

Exurban development is the fastest growing form of land use in the southeastern US and the primary driver of habitat and biodiversity loss. Species with long generation times such as the eastern box turtle (*Terrapene carolina carolina)* can persist in an urbanizing environment but have higher mortality than in forested habitat and show a response lag which delays detection of population decline. I quantify land use and land cover change over a forty year period by photo interpreting historic imagery that is orthorectified using a direct linear transformation model. A GIS database is created for three study sites and landscape pattern analyzed to determine the effects of historic land use on the eastern box turtle habitat using a suite of landscape metrics. A core habitat loss model is created using the *core* patch metric and box turtle life history traits, home range diameter, dispersal distance and re-generation. Spatial structure of fragmentation across time is characterized using global and local autocorrelation statistics and residual analysis of ordinary least squares (OLS) and geographically weighted regression (GWR) models using core as dependent variable and area, perimeter and mean slope as independent variables. Increasing fragmentation and road density over time is indicated by the landscape metrics for site 2 and 3. Regression model residual analysis suggests that the fragmentation trend at site 2 is clumped and scattered at site 3. All three sites lost forest and agriculture area and show an increase in urban and transportation area. Significantly 20% of the area of site 2 is being converted to urban land use since 1963. The rate per year of core forest loss at site 1 and 2 is decreasing and increasing at site 3 where the highest rate per year of core forest habitat loss was 8% between 1997 and 2007. Rate of core habitat loss per year is decreasing at site 1 and 3 and increasing at site 2 which lost 6% between 1997 and 2007. These rates of habitat loss suggest

that site 1 could sustain three generations of box turtles until all core habitat has disappeared. However, sites 2 and 3 could not sustain one generation of box turtles until all core habitat is gone.

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LIST OF ABBREVIATIONS

AIC_c	corrected Akaike Information Criterion
AVHRR	Advanced Very High Resolution Radar
DEM	Digital Elevation Model
DLT	Direct Linear Transformation
dpi	dots per inch
ESDA	Exploratory Spatial Data Analysis
GIS	Geographic information system
GWR	Geographically Weighted Regression
ha	hectare
km	kilometer
Landsat MS	Landsat Multispectral Scanner
Landsat TM	Landsat Thematic Mapper
LISA	Local Indicator of Spatial Autocorrelation
LTER	US Long Term Ecological Research Network
LULC	land use land cover
MMU	Minimum Mapping Unit
NDVI	Normalized Difference Vegetation Index
NVCS	National Vegetation Classification System
OLS	Ordinary Least Squares
RMSE	root mean square error
TWRA	Tennessee Wildlife Resource Agency
txline ROW	transmission line right of way
TVA	Tennessee Valley Authority
USGS	United States Geological Survey
UTM	Universal Transverse Mercator

INTRODUCTION

Exurban and Edge Effects

For the first time in a century there are more people moving to rural areas than into cities, which places increasing pressure on the wildland-urban interface (Brown et al. 2005, Hansen et al. 2005, Turner et al. 2003, Wear and Greis 2002). Exurban development, that is, low-density housing (< 25 homes/km^2) in a landscape dominated by native vegetation occurs along major roads and in isolated natural areas, resulting in fragmentation of the rural landscape (Hansen et al. 2005, Weng 2007). This type of development is the fastest growing form of land use in the United States, and has increased from 5% of land in 1950 to 25% in 2000 (Brown et al. 2005). Land use change of this form in the southeastern United States impacts the juxtaposition of land cover types by fragmenting and reducing the core interior of a once contiguous forest. Moreover, introduction of *edge effects* can profoundly impact how free ranging organisms use and move through a heterogeneous landscape (Dale et al. 2005, Hilty et al. 2006).

Biodiversity Loss and Fragmentation

The unprecedented scale of natural areas converted for human use is the primary driver of biodiversity loss (Forman and Godron 1986, Gagne and Fahrig 2007, Gardner and Urban 2007). Specifically, smaller and less vagile vertebrates such as amphibians are declining regionally and globally due to habitat loss (Vos and Chardon 1998, Blaustein et al. 1994, Gibbons et al. 2000). Rate of habitat loss may impact wildlife populations more than the actual loss or fragmentation of habitat (Schrott et al. 2005a). Species with long generation times such as the eastern box turtle (*Terrapene carolina carolina*) can persist in an urbanized environment but suffer higher mortality than in forested habitat and show a response lag to habitat loss which delays detection of population decline (Budischak et al. 2006, Dodd 2001, Ernst et al. 1994, Fahrig 2001). Turtles being K-selected vertebrates are characterized by long lives, low recruitment rates and delayed sexual maturity with high adult survival rates, making mature individuals persist for long periods within the landscape (Congdon et al. 1993). Because of their specialized mobility and habitat specificity, many box turtle populations in eastern North America exist in isolated forest fragments in urban and suburban areas (Nazdrowicz et al. 2008, Klemens et al. 2000) and can become functionally extinct (Dodd 2001, Wilson pers. comm.).

Landscape Pattern and Fragmentation

Within the current context of rapid landscape change, there are few studies of the specific effects of urban and exurban expansion on biodiversity (Hansen et al. 2005). Miller and Hobbs (2002) reviewed 217 landscape studies in recent volumes of Conservation Biology and only 6% are related to exurban and urban land use. There is an urgent landscape management need to understand and predict the impact of exurban development and increased road density on the rate of habitat loss and the effects on biodiversity (Hawbaker et al. 2006, Schrott et al. 2005a). In response to this need, there is a growing demand by public and private conservation and land management organizations for quantitative data of landscape pattern change and habitat fragmentation for effective conservation policy guidelines (Gustafson 1998, Turner et al. 2001, Vos and Chardon 1998).

Rates of Habitat Loss

Landscape ecological theory suggests the rate of habitat change is more critical to wildlife population viability than the pattern of change (Forman et al. 2003). The rate of habitat loss is unique to each landscape and cannot be extrapolated from landscapes that have similar amounts of habitat and fragmentation but dissimilar disturbance histories (Schrott et al. 2005b). When the rate of landscape change exceeds the re-generation time of the species, populations may exhibit a lagged response to habitat loss (Schrott et al. 2005a**).** The rate of change is a spatio-temporal gradient which varies across a landscape and is site specific (Schrott et al. 2005a). An important research priority is the rate of disturbance patterns in the landscape such as an increase in road density (Forman et al. 2003).

Roads Density and Small Vertebrates

Exurban development increases road density which bisects otherwise continuous habitat. Animal populations are fragmented by roads which can act as barriers to animal movement either through avoidance or mortality (Forman et al. 2003, Shepard et al. 2008a). Road kill of small vertebrates is not well documented when compared to large mammals (Trombulak and Frissell 2000). However, Allard (1935, 338) reported from the Washington DC area that "the great scourge in the box turtle's life" is getting crushed by passing cars on the highways; and Klemens (2000, 22) defines roads as a box turtle "kill zone". Reptiles and amphibians that have seasonal migrations as part of their natural history are particularly vulnerable to roads (Aresco 2003, Dodd 2001, Fahrig et al. 1995, Gibbons et al. 2000, Shepard et al. 2008b, Steen and Gibbs 2003, 2004, Steen et al. 2006, Trombulak and Frissell 2000). Mortality of female fresh water turtles when crossing roads on nesting migrations can be the cause of populations in the US to be increasingly male biased which will make turtle populations decline (Steen and Gibbs 2004, Steen et al. 2006). For example, the mortality rate of turtle populations in the southeastern US is partly due to road fatalities that are greater than 5% annually, and exceeds sustainable levels (Steen and Gibbs 2004). Road density in the US is ~ 6.5 million km, and exerts a significant ecological footprint on the landscape (Forman et al. 2003). Negative effects of roads are often underestimated but are recognized as drivers of land use change and habitat fragmentation (Hawbaker et al. 2006, Turner et al. 1996, Vos and Chardon 1998).

Habitat and Landscape Change Detection Rationale

Land cover data compiled from satellite imagery (i.e., Landsat TM and MS; espionage), aerial photography, a combination of the two or computer-simulated landscapes are traditionally used for landscape pattern analysis (Bürgii et al. 2002, Pearson et al. 1999, Tidd et al. 2001, Turner et al. 1996, Wear and Bolstad 1998, Wickham et al. 2007; (Appendices A-1 & 2). Whether using historic aerial photography or satellite imagery there are restrictions to consider. Fewer landscape studies strictly use historic aerial photography because of availability and resolution constraints (Freeman et al. 2003, Hawbaker et al. 2006, Bartell et al. 2002). The earliest systematic collection of satellite imagery is in 1972 from Landsat 1, and is limited by insufficient spatial resolution. While conducting national level landscape change studies for the US Geological Survey, Brown et al. (2005) remarks that Landsat imagery lacks the resolution to detect changes in natural habitats within metropolitan areas. Another source of error with satellite imagery is the difference in solar illumination of rugged terrain (Nichol and Wong 2008). The use of spectral signature algorithms, i.e., Normalized Difference Vegetation Index

(NDVI) introduces another potential source of misinterpretation error. For example, a Loblolly Pine plantation, which is a commercial or agricultural land use, would have the same signature as a natural conifer forest. However, manual photo interpretation would distinguish the consistent row pattern to be a manmade and not natural construct (Lillesand et al. 2008). These shortcomings of satellite imagery however, are offset by the resource intensity of manual photo interpretation and the project specific availability of aerial photography.

Landscape pattern and habitat fragmentation analyses are customarily conducted using traditional landscape metrics software programs such as Fragstats (Fragstats Landscape Ecology Program *vers*. 3.3-4; McGarigal et al. 2002). More recently, landscape ecologists are using spatial statistics and spatial regression models for species and habitat studies to explore the spatial effects of autocorrelation and heterogeneity in spatial data (Fotheringham et al. 2002, Legendre 1993). Heterogeneity of a landscape impacts organisms when their habitat is fragmented and *edge effects* and dispersal distances are important (Hilty et al. 2006, Turner et al. 2001).

Spatial Effects and Land Use Change Data Rationale

Spatial structures are traditionally considered by ecologists more of a nuisance than source of information about the landscape (Legendre and Fortin 1989). There are two main categories of spatial effects, which are spatial autocorrelation, that is, correlations among neighbors over space, and spatial heterogeneity, which is variation over space (Zhang et al. 2008). With spatial data, there usually is a relationship between variables that is location dependent, that is, different from one location to another. Spatial heterogeneity (non-stationarity) is when the linear relationship between variables is not constant across the geographic area of interest (Zhang et al. 2008). This patch dynamic is a process which varies in space and time as a result of disturbances that differ in frequency, intensity, size and shape (Turner et al. 2001). "Spatial structure is a mix of both induced spatial dependence (i.e., variable response to the spatial structure of exogenous process) and inherent spatial autocorrelation (i.e., inherent in the ecological process of the variable of interest)" (Fortin and Dale 2005, 124).

Global Moran's I is used to determine autocorrelation and is similar to Pearson's correlation coefficient, whereas the Local Moran's I (LISA) statistic shows how neighboring values are associated with each other (Fortin and Melles 2009). The LISA statistic complements Fragstats classification based analysis in interpretation of the spatial arrangement of data in the landscape (Southworth et al. 2004). Geographically Weighted Regression (GWR) is a relatively recent addition to the spatial ecology toolbox and is used to model wildlife distribution, land use change, climate change, forestry stands and is used with landscape metrics (Cho et al. 2009, Foody 2003, Foody 2004, Fortin and Melles 2009, Guo et al. 2008, Kimsey et al. 2008, Kupfer and Farris 2007, Osborne and Suárez-Seoane 2002, Osborne et al. 2007, Platt 2004, Shi et al. 2006, Wimberly et al. 2008, Zhang et al. 2008).

Research Objectives

The spatial structure of Hamilton County is strongly influenced by the ridge and valley topography of the Tennessee Valley, with its closely furrowed ridges that have a northeast-southwest trend and the flood plain of the Tennessee River which cuts the county in half. The southeastern limits are defined by steep forested slopes of the Appalachian Mountains and its northwestern limits by the Cumberland Plateau Escarpment (Amick 1934). I am choosing three study sites located in northern Hamilton County to process and photo interpret 40 years of historic aerial photography to create a set of temporal land use and land cover datasets. Specific objectives Include:

1. Create orthorectified imagery using fine scale historic aerial photography over the last 40 years at three sites in Hamilton County that is suitable for photo interpretation.
2. Photo interpret imagery using a land use land cover (LULC) classification scheme and creating a GIS database that can be implemented in a temporal and box turtle habitat model analysis.
3. Create eastern box turtle and temporal LULC change models that can be fitted to statistical analysis.
4. Perform analysis using landscape ecology metrics, autoregressive and spatial statistics and map fragmentation patterns and box turtle habitat change that will expedite inferences about fragmentation trends and box turtle conservation.

METHODS AND MATERIALS

Study Site Descriptions

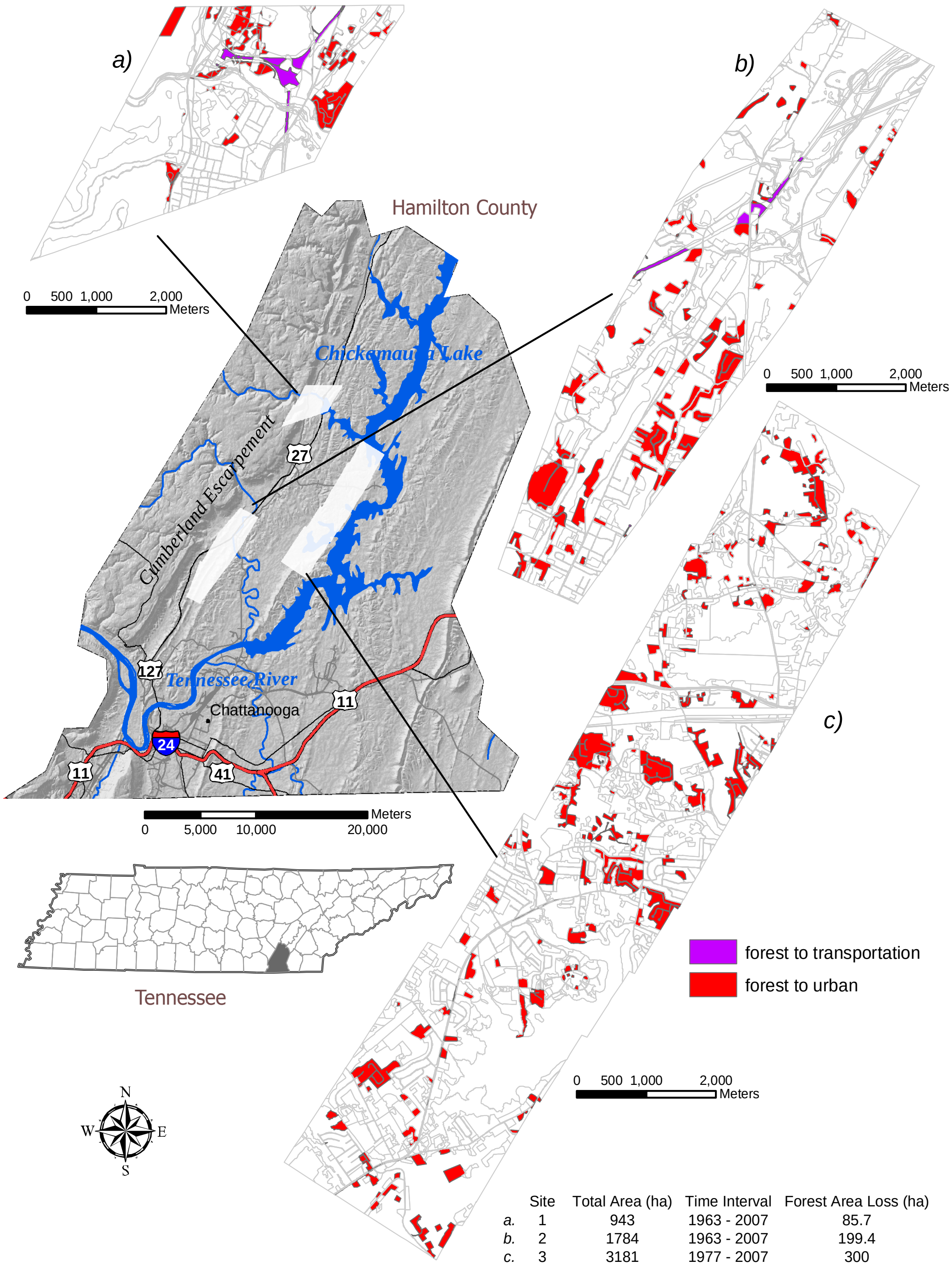
Site 1 was in the Soddy Daisy Municipality, flanked on the northwest by the Cumberland Escarpment and on the southeast by Highway 27 and encompassed the old town of Soddy and the Highway 111 / 27 Interchange. The southeast was bounded where Soddy Creek empties into Soddy Lake and was in the Soddy Creek Watershed. Dominant forest communities on the drier slopes of the Cumberland Escarpment are Dry-Mesic Oak of Middle and East Tennessee (Hinkle 1989, quoted in Tennessee GAP Analysis Land Cover Manuel 2006) and Loblolly Pine

Plantation (pers. obs.). Mixed Mesophytic Hardwood Forest is in protected areas of the escarpment slopes, coves and deep ravines (Hinkle 1989, quoted in Tennessee GAP Analysis Land Cover Manuel 2006). The lower elevations were predominately open land with small upland patches of Xeric to Mesic Mixed Conifer/Hardwoods (Figure 1).

Site 2 was in the Chattanooga Municipality between the Soddy Daisy and Red Bank Municipalities, flanked northwest by the Cumberland Escarpment and Highway 27, centered around the Highway 153 and the 27 Interchange and North Chickamauga Creek. It was in the Lower North Chickamauga Creek Watershed. Dominant forest communities are Dry Mesic Oak Forest and Xeric-Dry Oak Forest of Middle and East Tennessee mixed with open land in the lower elevations.

Site 3 encompassed the Lakesite Municipality, approximately 70% is unincorporated. The southern end included Dallas Bay and the northern tip of Big Ridge which at 305 m was the highest elevation in site 3. Tennessee Valley Authority (TVA) Sequoyah Nuclear Plant was approximately 0.9 km (0.6 miles) east. This site was in the Tennessee River Watershed. Dominant forest communities were Dry Mesic Oak Forest and Xeric-Dry Oak Forest of Middle and East Tennessee and there was a patch of White Pine/Hemlock Forest in the northern area of the site.

The above mentioned floristic references of tree species were from the National Vegetation Classification System (NVCS) vegetation alliance grouping of the TNveg database Metadata (Tennessee GAP Analysis Land Cover Manuel 2006; Appendix C).



	Site	Total Area (ha)	Time Interval	Forest Area Loss (ha)
a.	1	943	1963 - 2007	85.7
b.	2	1784	1963 - 2007	199.4
c.	3	3181	1977 - 2007	300

Figure 1. Vicinity map of study sites in Hamilton County, Tennessee**. a)** Site 1 was in the Soddy Creek Watershed. This site was bound by Highway 27 on the southeast and on the northwest by the Cumberland Plateau. **b)** Site 2 was in the Lower North Chickamauga Creek Watershed, also along Highway 27 around the Highway 153/27 Interchange and North Chickamauga Creek. **c)** Site 3 was in the Tennessee River Watershed, with Dallas Bay and the northern tip of Big Ridge along the southeast boundary.

Spatial pattern of geophysical phenomena has been reported to influence data with anisotropy, a spatial effect that had a dominant gradient and will be reflected in the metric results (Gustafson 1998, Wu et al. 2002). My study areas had a northeast to southwest trend following the ridge and valley topography of Hamilton County, which was also mirrored by the study site linear rectangular shape, inherited from the aerial photography flight lines. This anisotropy may have precluded the application of parametric statistical analysis by violation of the assumption of stationarity of the data.

Data Acquisition

Countywide comprehensive coverage of panchromatic aerial photography for 1997 was readily available from the State of Tennessee Base Mapping Project, and 2007 color orthophotography was obtained from Aerials Express (a private consultant). Historic aerial film was obtained from the TVA Historic Aerial Photography Repository (Table 1). Study site selection was dictated by availability of photography, thus was not randomly chosen. However, this did not affect assumptions of statistics because the extent of each site was exhaustively sampled (Fortin and Dale 2005); but, selection of parametric tests and landscape indices was sensitive to site extent and spatial resolution (i.e., pixel size).

Orthorectification

Each 9 in. x 9 in. frame of film was scanned at 1000 dpi using a roll film scanner (Vexcel® Ultra Scan 5000). I then co-registered the historic frames to the 1997 orthophoto by selecting six to nine evenly spaced known tie points on the base orthophoto and selected that same point with precision on the historic aerial photo (Leica® Photogrammetry Suite Autosync

Table 1. Source list of aerial photography, DEM, road vector data. All of the historic aerial photography from the TVA Repository was the same scale 1:12000.

Date	Project	Scale	Resolution	Flight Altitude	Medium	Source
10/02/1963 03/11/1972 10/21/1977 06/09/1980 09/06/1984 02/21/1985	Dev. Hwy 27 Pump Storage Milfoil Studies Sequoyah Nuclear Plant Milfoil Studies Flood Studies	1:12,000 1:12,000 1:12,000 1:12,000 1:12,000 1:12,000	1.0 ft.	6,000 ft. above mean ground level	Historic panchromatic aerial photography 1984 color negative panchromatic	Tennessee Valley Authority Repository
1997	~	1:30,000 1:7,600	2.0 ft. 0.5 ft.	~	Orthophoto created from panchromatic aerial photography	State of Tennessee Base Mapping Program
5/1/2007	~	~	0.5 m	12,600 ft. above mean ground level	Digital color orthophoto from aerial digital camera	Aerials Express
1997	~	~	~	~	Hamilton County Parcel Data: Edge-of-pavement line shapefiles	Hamilton County GIS Department
04/2007	~	1:24,000	10 m	~	National Elevation Data (NED)	USDA/NRCS (downloaded from Data Gateway)

software Version 9.1; Okeke and Karnieli 2006). The easiest locations for placing manual control were road intersections because they usually had not relocated through time and stood out on the low contrast historic photos (Freeman et al. 2003). I looked for tie points located within the 60% overlap of the historic photos. I chose a Direct Linear Transformation model to geometrically correct the input images. This model was a good approximation for frame cameras without calibration reports and it used a DEM for 3D transformation to automatically place control points (Leica 2007). Each registered historic photo was “draped” over a 10 m resolution DEM to reduce vertical displacement (Leica Geosystems Imagine Autosync™ 9.1 software, 2007; Freeman et al. 2003, Wear 1998). During the process of solving the model, each photo was geographically referenced with each control point from both the base and the historic images and tie points were automatically generated (an average number of 125 tie points).

The accuracy of how well the calculated solution of the rectification process fitted the original data was a measure of the residual of the x and y axes for each control point and was reported with a root mean square error determination (RMSE) value. I reviewed these results, deleting points with a RMSE > 8 m. In some cases, I deleted or adjusted manual points and re-ran the model for a better fit. RMSE errors reported were often not connected with positional errors so they could be misleading. Hence, it was possible to collect too few control points and still maintain a low RMSE (Rocchini and Di Rita 2005) so it was necessary to visually inspect the rectified historic image with the ortho-rectified reference image. I re-sampled the block, and repeated this process for each historic frame of film. I then edge matched the resulting individual orthophotos to create a mosaic for each study area with 0.5 m pixel resolution, projected into Tennessee State Plane North American Datum (NAD83) with units in feet (Freeman et al. 2003).

Temporal Resolution

Transportation vector data was obtained from the parcel mapping component of the State of Tennessee Base Mapping Project for 1997. I photo interpreted land cover features from the 1997 orthophoto first because this dataset would be the template (point of departure) for the subsequent datasets. The land cover features were classified with a modified Anderson classification system using the heads-up digitizing technique (Table 2). On screen photo interpretation was supplemented with a stereoscope to obtain synoptic view. The minimum mapping unit (MMU) used was 0.5 hectare.

I copied the 1997 dataset to create the next dataset and modified it with that year's imagery. If a polygon was unchanged, I left it alone, according to methodology used by Comber et al. (2003). This was an iterative process of deleting, reshaping or adding features to conform to the imagery. This process was repeated for each study site for each year, which resulted in thirteen datasets. Overall, the technique of using each dataset as template for the next dataset avoided some of the common cartographic issues and uncertainty that could arise when the same area was mapped on two occasions.

Data Clean up and Metrics

I analyzed the datasets using Fragstats landscape metrics at three levels – feature (patch, class (land use land cover (LULC) type) and landscape (year). I used a subset of these metrics which considers patch type adjacency, (such as the calculations of nearest neighbor), or were

Table 2. Classification Code is Modified Anderson Classification System (Anderson et al. 1976).

Code	Type	Description	% Cover Scale
1	Urban	Residential, commercial, light industry	50-100%
14	Transportation	Roads, railroads, airports	100%
145	Txline ROW	Electric transmission right of way	100%
2	Agriculture	Pasture, crops	50-100%
3	Range land	Shrubs and/or small trees, usually 0.5 to 5 m tall with individuals or clumps widely spaced not touching generally forming >25% canopy cover	50-100%
4	Forest	Trees usually over 5 m tall, crowns interlocking	60-100%
47	Plantation	Commercial tree farm	100%
5	Water	Lakes, ponds, rivers	100%
6	Wetland	All wetlands	100%
7	Barren land	Disturbed, without structures or vegetation cover	100%

based on edge length to calculate segments that represent true edge. However, these metrics did not recognize when segments are artificially truncated by the study boundary (McGarigal et al. 2002). In order to address this problem, I created a buffer strip (i.e., border), which surrounded the study area boundary of each dataset. This border strip area was not calculated in other metrics involved in the analysis (i.e., such as area quantification). Effects of the artificial edge imposed on patches by the site boundary were mitigated by this process (Gustafson 1998).

I created an edge depth file with the *core* patch metric to measure what constituted the core area of a habitat patch (Table 3). The edge depth file was a resistance coefficient matrix which represented the distance at which edge effects penetrated into a patch. This weighting scheme provided unique edge depths (m) for each edge type (i.e., each pair wise combination of patch types). Resistance coefficients in the *core* metric specified edge depth at 300 m between non-habitat matrix (i.e., roads, urban) and 0 depth between habitat matrix (i.e., forest, agriculture, transmission line right-of-way (txline ROW).

Accuracy Assessment

Uncertainty issues of polygon boundary detection in land cover mapping have been reported in the literature to compound with land cover change analysis and can lead to inappropriate inference in subsequent analysis (Lo and Yeung 2007, Longley et al. 2001). Hence, accuracy assessment was impacted by a variety of factors which were magnified with land cover change maps. Examples of such influences were conditions at the time of image acquisition, mis-registration of datasets, thematic classification error and aggregation of heterogeneous polygons (Foody 2002).

Table 3. Edge weight file used with *core* metrics. The buffer around potential core turtle habitat patches agriculture, rangeland, forest, plantation, wetland and txline ROW was the maximum 300 m when these patch boundaries were coincident with transportation patches. All transportation and urban patches had 0 m buffer. The 50 m was for patches coincident with water and when certain potential core habitat patches were coincident with each other.

Numeric	Land Use Class	1	2	3	4	47	5	6	7	14	145
1	Urban	0	0	0	0	0	0	0	0	0	0
2	Agriculture	50	0	0	0	50	0	0	0	300	0
3	Rangeland	50	0	0	50	50	50	50	0	300	0
4	Forest *	300	0	0	0	0	0	0	50	300	0
47	Plantation	300	50	50	0	0	50	0	50	300	0
5	Water	50	50	50	50	50	0	50	50	50	50
6	Wetland	300	50	50	0	0	50	0	50	300	50
7	Barren	0	0	0	50	50	50	50	0	300	50
14	Transportation	0	0	0	0	0	0	0	0	0	0
145	Txline ROW	300	0	0	0	0	0	0	0	300	0

*Focal habitat patch

After all land cover maps were completed, assessment of attribute and thematic accuracy was estimated by an independent, expert photo interpreter employed by TVA. Sampling locations were randomly selected, comprising 10% of the total dataset area with an accuracy requirement of 90% of each sample. This was within the US National Map Accuracy Standards for horizontal ground accuracy of geospatial data that USGS specified for maps on publication scales larger than 1:20,000 and not more than 10% of the points tested could be in error by more than 0.03333 inch (0.1 cm) on the map. I used the equation:

$$0.03333 \times 12{,}000 \times 2.54 / 100$$

This would be 10.2 m on a 1:12,000 scale map. (US Geological Survey http://rockyweb.cr.usgs.gov/nmpstds/nmas.html accessed 10/31/2009).

Development of Box Turtle Habitat Model

Life history records and observations of the eastern box turtle have reported that the eastern box turtle used multiple habitat types, mesic forests for thermoregulation and overwintering, and fields and open areas for nesting sites and basking (Dodd 2001, Ernst et al. 1994). As a habitat generalist, *T. c. carolina* has been reported to have less restrictive habitat requirements for dispersal than a specialist. I developed a habitat model for the eastern box turtle to explore how habitat loss affected the capacity of the landscape to support theoretical box turtle populations (Schrott et al. 2005a). Empirical data on the eastern box turtle's spatial ecology for Hamilton County was absent, but life-history derived from the literature could be used as a surrogate (Congdon et al. 1993, Pearson et al. 1999). I was specifically interested in these traits: area sensitivity, home range size, dispersal ability, foraging habits and length of time for cohort re-generation (Schrott et al. 2005a; and see Appendix B).

A box turtle's success in traversing an inhospitable or (i.e., roads, subdivisions, etc.) sub-optimal (i.e., plantation and transmission line ROW) matrix will be influenced by the distance to the patch and the turtle's ability to find a corridor through the matrix (Hilty et al. 2006). I averaged the home range diameter and dispersal distance of the eastern box turtle that was reported in the literature which resulted in a home range area with a 266 m diameter (Table 4). Therefore, I defined the box turtle minimum home range diameter and dispersal distance as 300 m (Bender et al. 2003). The radius distance parameter of the proximity patch metric also was defined as 300 m. Hence, the proximity metric measured the distance between patches that represented the dispersal capacity of the box turtle on average (Bender et al. 2003, Dodd 2001, Dolbeer 1971, Donaldson and Echternacht 2005, Ernst et al. 1994, Gustafson and Parker 1994, Gustafson et al. 1994, Stickel 1989). The *edge effect* response I modeled for box turtles was based on their lack of avoidance of edges that acted as dispersal barriers (i.e., roads), and subsequently, box turtles needed additional protection from the effects of edges.

Core Habitat and Edge Effects

In this model the capacity of the landscape to support box turtle populations was measured by the amount of forested habitat that was not juxtaposed to roads and urban development. A margin of safety interfacing a core box turtle habitat patch and an inhospitable matrix was defined using a 300 m buffer. In this scenario, the matrix functioned as a dispersal sink between habitat patches (Hilty et al. 2006) because the matrix was either sub-optimal or inhospitable, large relative to the habitat patches and the distance between habitat patches can be large. Edges that were adjacent to potential open areas for nest site selection by females were not assigned a weight in the edge depth between a forest patch and agriculture, range, plantation and txline ROW because I wanted to make a distinction between hospitable and inhospitable matrix (Table 4). The landscape metric parameters for the core habitat model were:

- *Proximity* measure > 1000 (unit less)
- *Core* > 0 (ha)

Potential box turtle land use classes were *Forest*, *Agriculture*, *TXline ROW, Wetlands*, *Plantation and Rangeland*. Each box turtle habitat subset was created by deleting all *core* patches with values less than 0 and those that had *proximity* values less than 1000 (Microsoft Office Excel 2007). *Proximity* values were relative, the larger value associated with a clumping of the focal patch.

Vulnerability to Habitat Loss

This model evaluated the sensitivity of the box turtle response to habitat loss. The ability of a box turtle population to persist in the landscape has been reported to be affected by the rate of habitat loss which was calculated from current and historic land use change. The vulnerability threshold has been defined as a measure of sensitivity to the rate of habitat loss and was calculated by scaling the rate of box turtle re-generation time (λr) to the rate of habitat loss (r) (Schrott et al. 2005a). Rate of habitat loss was calculated by dividing the habitat change (Δh = total area) of habitat lost within x number of years (h) by x number of years that have lapsed (Y^a)) by the total core area (ha) of habitat of the previous decade (h^a).

$$r = [(\Delta h) / h^a)]$$

The definition of box turtle re-generation time I employed in this model was the average length of time between birth of an individual and the age its own offspring reproduced (Table 5).

Table 4. Summary of *Terrapene carolina carolina* home range statistics from literature but see Ernst et al. 1994, Dodd 2001

	Area (ha)				Linear Distance (m)	State	Reference
	Range	*Mean*	*Min.*	*Max.*			
1	0.3 – 0.6	~	~	~	89 – 265	TN	Davis 1981
						TN	Dolbeer 1971
2	1.88 (±.49)	~	0.28	6.5	~	TN	Donaldson et al. 2005
3	~	~	~	~	228	NY	Nichols 1939
4	~	~	~	~	167	PA	Strang 1983
5	~	~	~	~	171 ♂ 176.4 ♀	IN	Williams et al. 1987
6	1.20 ♂ 1.13 ♀	~	~	~	~	MD	Stickel 1989
7	~	174	57	469	~	MD	Hall 1999
			Outside 300 m Home Range				
1	~	323	0	408	~	MD	Hall 1999
2	~	~	~	~	457-716	MD	Stickel 1989
					Summed Average **266**		

Table 5. Cohort re-generation sources used to determine the box turtle re-generation time and to calculate the lagged response of a population to the rate of habitat loss.

Species	Age at reproductive maturity (yrs.) (α)		Cohort generation time (yrs.)	Annual Rate	Annual Pop. Growth Rate (λ)	Source
	range	*mean*	*mean*			
Emydoidea blandingii	14 to 20		37.5	0.03		Congdon et al. 1993
Terrapene carolina carolina		20.0				Wilson pers. obs. (unpubl. data)
Terrapene carolina carolina		18.0				Ernst et al. 1994
Clemmys insculpta	14 to 18	16.0				Ernst et al. 1994
Chelydra serpentina	11 to 16	12.0	25	0.04		Congdon et al. 1994
Clemmys insculpta		12.0				Garber et al. 1995
Terrapene ornata ornata					1.0060	Converse et al. 2005
Terrapene carolina ornata					1.0200	Bowen et al. 2004

I used Congdon's cohort generation time of 37.5 years because the reproductive ecology of *Emydoidea blandingii* was similar to *Terrapene carolina carolina* (Wilson pers. obs).

Box turtle re-generation time was calculated as:

$$\boldsymbol{\lambda r} = 1/37.5 = 0.03 \text{ (2.67\%/yr.)}$$

Number of generations of box turtle until core habitat = 0

$$[h / (\mathit{cumulative}\ \Delta h)(\boldsymbol{\lambda r})]$$

Box turtle populations have been reported to exhibit a lagged response to habitat loss when the rate of loss was greater than turtle re-generation rate:

$$r > \lambda r$$

Data Analysis

Landscape Change Pattern Analysis

Landscape metrics have been reported to be highly correlated, and most of the variation of spatial heterogeneity in landscape pattern has been explained by five independent compositional components which were: average patch compaction, overall image texture, average patch shape, patch perimeter-area scaling and number of attribute classes (Riitters et al. 1995). Eastern box turtle core habitat was quantified with the following patch level metrics, which were:

1. *area*
2. *core*
3. *perimeter*
4. *proximity index*

The *core* metric was a very useful metric in determining core habitat patches coincident with non habitat patches because it selectively defined a buffer around the habitat patch. The *proximity* metric did a good job of determining patches within proximity of other habitat patches, however, did not adequately differentiate between inhospitable matrix (i.e., roads, which were essentially dispersal barriers) and hospitable matrix.

Because each study site was a magnitude larger than the next, I chose metrics that showed consistent and linear scaling relations with respect to extent and could be extrapolated or interpolated across spatial scales for comparisons between study sites (Wu 2004). Fragstats class level metrics were evaluated for pattern analysis via graphs and bar charts. The metrics used to make comparisons between study sites were as follows:

1. *total edge*
2. *number of patches*
3. *class area*
4. *landscape shape index*

For characterization of fragmentation patterns across each study site, I included the following indices:

1. *patch density*
2. *largest patch index*
3. *area weighted mean patch size*
4. *area weighted mean shape index*
5. *area weighed mean core area index*

The *mesh* landscape level metric was used to characterize road density and rate of fragmentation across the landscape of each study site. Forman et al. (2003) have described *mesh* size, the area of patches enclosed within a network, as an effective measure of how road systems have affected the landscape. *Mesh* size was defined to be inversely related to road density. Road density equaled the total length of roads in unit area (Forman and Godron 1986, Hawbaker et al. 2006), as road density increased, *mesh* size shrank. Effective *mesh* size included the parameters of pattern and width of road zone, as fragments got smaller, the landscape would get more patchy and isolated (Forman and Godron 1986). Effective *mesh* size has been used as a suitable proxy measure for assessment of relationships between structural properties, landscape function and the direction of landscape change (Jaeger 2000). I listed all Fragstats metrics used in the statistical analysis with their acronyms in Table 6, and Appendix C can be referenced for complete metric derivation.

Statistical Analysis

Normality and homogeneity of variance of dependent variables were tested and when those assumptions were not met, I $\log_{10}$ transformed the data. Each study site was analyzed separately because of the varying extents. Variables used in this analysis were:

1. *area_log*
2. *perim_log*

Categorical variables used:

1. *yr*
2. *type*

The effect of time on the area and perimeter of patch types *Agriculture, Forest, Urban and Transportation* was tested with a Repeated Measures first order autoregressive model with PROC MIXED (SAS Institute Inc., 2008; $\alpha = 0.05$). Proc Mixed estimated the covariance parameters using the method of restricted maximum likelihood (REML). The first-order autoregressive covariance structure has been used for observations that have been more highly correlated when they were closer in time than when farther apart. Time series data has been reported to be autocorrelated and the effect on regression models could inflate the estimates of

Table 6. Fragstats metrics with their acronyms. (a) Patch, level metrics used to measure eastern box turtle habitat change. (b) Class level metrics for descriptive statistics, characterizing fragmentation. (c) Landscape level *mesh* metric characterized road density. See Appendix C for definitions of each metric.

a)

Patch Level	
Area	*(AREA)*
Proximity Index	*(PI)*
Euclidian Nearest Neighbor	*(ENN)*
Shape Index	*(SI)*
CORE	*(CORE)*

b)

Class Level	
Class Area	*(CA)*
Number of Patches	*(NP)*
Total Edge	*(TE)*
Landscape Shape Index	*(LSI)*
Patch Density	*(PD)*
Percent of landscape	*(Pland)*
Largest Patch Index	*(LPI)*
Area Weighted Mean Patch Size	*(AREA _AM)*
Area Weighted Mean Shape Index	*(SHAPE_AM)*
Area Weighted Mean Core Area Index	*(CAI_AM)*

c)

Landscape Level	
Mesh	*mesh*

coefficients (Hawbaker et al. 2006). Autoregressive models incorporated correlation structures to account for autocorrelation.

I used a Student's Paired T-Test to test the relationship of variable *area_log* of *forest* and *agriculture type* with *area_log* of *urban* and *transportation type* (Microsoft Office Excel 2007; one-tailed, $\alpha = 0.05$; $df = 4$, Site 1; $df = 3$, Site 2 and 3). Each dataset was tested with Mauchly's Criterion test for sphericity between *year* and *type (area_log)* using PROC GLM and for autocorrelation I used a generalized Durbin-Watson Statistic test with PROC AUTOREG (SAS Institute Inc., 2008; $p < .0001$).

Exploratory Data Analysis

It has been recommended that it is a good idea to conduct exploratory spatial data analysis (ESDA) to get an overview of trends with the datasets, such as autocorrelation and heterogeneity (Fortin and Melles 2009, Fotheringham et al. 2002, Johnston et al. 2001, Longley et al. 2001, Wong and Lee 2005). Global statistics have been reported to assume that spatial relationships were constant across space which may be problematic if there were geographic differences in the relationship (Brunsdon et al. 1996). Spatial statistics have been reported to offer an option to map and describe spatial variation. The inclusion of spatial statistics and models in landscape ecology research could complement traditional metrics applications and may be of increasing interest to landscape ecologists (Kupfer et al. 2007, Southworth et al. 2004).

In this study, spatial structures (autocorrelation and heterogeneity) were considered part of the ecological process under investigation (Legendre 1993). I used spatial statistics to derive pattern and rate of land use change and I evaluated normality of the variables with histograms.

The linear relationship between dependent and independent variables was evaluated with scatter plots and collinearity between indicator variables was evaluated with Pearson's Product Moment correlation coefficients (SAS Institute Inc., 2008; $\alpha = 0.05$). I constructed separate Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models for each dataset to explain fragmentation of core habitat over time. Autocorrelation and heterogeneity were assessed by calculating Global and Local Moran's I statistics (ESRI ArcGIS 9.3 Spatial Analyst, 2008).

I created a new variable for spatial regression analysis:

mean slope, which was extracted from a USGS 30 M digital elevation model (DEM). This variable was used as a weight in the models to specify topography influences in each study area (Tables 7-1 & 7-2).

Variables used in spatial analysis were:

1. *core*
2. *area*
3. *perim*
4. *mean_slope*

Core, area and *perim* were derived from the Fragstats analysis. The dependent variable in these regression models was *core*, which measured the effective patch size after it was buffered 300 m from transportation or urban polygons (Hilty et al. 2006). This variable was the basis for the box turtle core habitat analysis. Indicator variables were *area*, *perim* and *mean slope*. *Area* was patch area in hectares and was the principal component that made up the core area. *Perim* was the perimeter of each polygon in meters and was a measure of edge, which contributed to the shape and location of patches (Hawbaker et al. 2006). The variable *mean*

Table 7-1. Description of derivation of variables *Area_log, Perim_log* and *mean_slope*.

Variable	**Description**
Area_log	*Area m^2 Log10 transformed (all land use classes).*
Perim_log	*Perimeter/Area ratio Log10 transformed*
Mean_slope	*Mean Slope - USGS 30 M DEM converted in ArcGIS Statistical Analysis to slope (degrees) shapefile polygon, spatial join (one to many) shapefile polygons in dataset to slope; create summary statistic table with frequency, mean, maximum, median, range and standard deviation in ArcGIS Spatial Statistics Toolbox; joined statistics table to dataset polygons. The field value is unitless (see Table 7F for GRIDCODE index).*

Table 7-2. *Mean Slope* variable values are the GRIDCODE, a unit less number representing the degrees of slope converted from the 30 Meter USGS DEM raster to a shapefile.

GRIDCODE	Degrees Slope
1	1-5
2	5-10
3	10-15
4	15-20
5	20-25
6	25-30
7	30-35
8	35-40
9	40-45
10	45-50
11	50-55
12	55-60
13	60-65
14	65-70

slope has been reported to influence the core area because of the relationship between land use and forest with slope (Fu et al. 2006, Kimsey et al. 2008).

The variable *core* had values of 0, so log transformation was not an option. Histograms for the *core* variable for each data site showed that this variable did not have a normal Gaussian distribution, and was skewed to the right with high kurtotic values. Variables *area* and *perim* had a normal distribution, although sites 1 and 2 were negatively skewed, albeit slightly, but *mean slope* was normally distributed (Appendix F). I did not transform the variable *core*, therefore, I did not log transform the other variables for analysis.

I tested three models which were:

Model	Dependent Variable	Independent Variable(s)
A	*core*	*area*
B	*core*	*area, perim*
C	*core*	*area, perim, mean_slope*

I created scatter plots with the dependent variable *core* on the y axis and *area, perim* and *mean slope* independent variables on the x axis to determine the relationship and created histograms of each variable to evaluate normality.

Measures of Autocorrelation

Regression model errors were assessed for autocorrelation by calculating Moran's I spatial autocorrelation coefficient for the residual errors (Fortin and Melles 2009, Kupfer et al. 2007, Zhang et al. 2008). I evaluated the GWR residuals for autocorrelation using the Global Moran's I and Local Indicator of Spatial Autocorrelation (LISA) (Anselin 1995). Heterogeneity was explored by analyzing coefficient of determination (R^2) and parameter coefficient values.

I assessed clustering and dispersal patterns in each dataset by calculating Global Moran's I autocorrelation coefficient at fixed distance bands 600, 900, 1200 and 1500 m to gain a baseline trend before regression analysis (ESRI ArcGIS 9.3, 2008; α 0.05); (Fortin and Melles 2009).

Moran's I has been defined by its variables:

$$\mathrm{I} = \frac{n\sum\sum w_{ij}\ (x_i - \bar{x})(x_j - \bar{x})}{W\ \sum(x_i - \bar{x})^2}$$

where x_i and x_j were values of the variable x at sampling location i and j; $\bar{x}$ was the mean value of the variable, W was the sum of w_{ij} i.e., the number of pairs of sampling locations per distance class; n was the number of sampling locations. (Wong and Lee 2005, Fortin and Melles 2009).

The Moran's I evaluated whether the pattern was clustered, dispersed or random, and values ranged from -1 (extreme negative autocorrelation) to 1 (extreme positive autocorrelation). The Global Moran's Coefficient was an average value of spatial autocorrelation for all spatial locations (Fortin and Melles 2009). I plotted the Global Moran's I coefficient values against distance classes in a correlogram to interpret characteristics of spatial pattern (Fortin and Dale 2005).

Ordinary Lease Squares Analysis

I used the global regression technique ordinary least squares (OLS) to explore the spatial relationship of *core* with *area*, *perim* and *mean slope*, and to gain a baseline trend of the pattern of change of core habitat over time.

The global regression model has been stated as:

$$y_i = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + \varepsilon_i$$

where y_i was the value of response variable y at location i. β_0 was the intercept, β_j was the slope coefficient for predictor variable j, x_{ij} was the value of predictor variable j at location i, and ε_i was the random error term (Kupfer and Farris 2007).

GWR Technique

Spatial non-stationarity of relationships between variables has been detected and accounted for with a GWR model because this technique allowed regression parameters to vary in space (Kupfer and Farris 2007, Leung et al. 2000). I used this technique to estimate local regression parameters (Brunsdon et al. 1996). The model for GWR was:

$$y_i = \beta_0 (u_i, v_i) + \sum_k \beta_k (u_i, v_i) x_{ik} + \varepsilon_i$$

where (u_i, v_i) was the coordinates of the ith point in space and $\beta_k (u_i, v_i)$ was the realization of the continuous function $\beta_k (u, v)$ at point i (Fotheringham et al. 2002). Briefly, the GWR estimation procedure was to draw a circle around a location ***i***, compute a weight for neighboring observations and estimate the model coefficients using a weighted least squares (Zhang et al. 2008, Leung et al. 2000).

Bandwidth Selection

The weighting function and kernel (i.e., bandwidth which defined the distance decay) selection were the most critical components of a GWR analysis because the slope parameter estimates between the independent variables and the dependent variable were influenced by their selection (Foody 2003). The wider the bandwidth the parameter estimates will tend toward a global estimate (Foody 2003), the smaller the bandwidth the parameters get increasingly variable. Previous experimental trial runs of GWR models with this data using fixed bandwidth distance lags showed that as the distance lag increased the corrected Akaike Information Criterion (AIC_c) values, Condition Index values, range of coefficient values, but the range of GWR model R^2 values decreased.

I used an adaptive kernel method to determine the best bandwidth and weighting function values and minimization of the AIC_c (Fotheringham et al., 2002, Foody 2003). The adaptive kernel adapted where data were sparse the bandwidth was larger and where data were more dense the bandwidth was smaller (Kupfer and Farris 2007). This was important for edges of the study area where the number of neighbors around a data point will often be relatively small (Brunsdon et al. 1996).

AIC_c was defined as:

$$\mathrm{AIC_c} = 2n \ \log_e(\hat{\sigma}) \ + \ n \log_e(2\pi) + n \left\{ \frac{\boldsymbol{n + tr(S)}}{\boldsymbol{n - 2 - tr(S)}} \right\}$$

where *tr(S)* was the trace of the hat matrix and *n* was the number of observations (Fotherington et al. 2002).

The GWR best fit model was determined for each site by examining R^2 and AIC_c scores. AIC_c was useful for comparing models with different independent variables but the same dependent variable (ArcGIS Spatial Statistics 2008). I ran several GWR iterations using various combinations of independent variables and compared AIC_c scores by examining the output. Between each study site, the model combination of independent variables with the best fit AIC_c

score varied. The best fit model had the lowest AIC_c score and a difference of at least three (Fotheringham et al. 2002).

Model Fit and Analysis

I explored differences in the coefficient of determination (R^2) values between each year of each study site to determine variation across the site for each regression technique. I mapped and analyzed the parameter coefficients for each independent variable for non-stationarity.

I tested for collinearity of GWR model coefficients using the variance-decomposition proportion and condition index diagnostic tool (Wheeler 2008). Coefficients with condition index values > 30 have been reported to be highly correlated with each other (ArcGIS spatial_stastics_tools 2009, Wheeler 2008).

GWR Model Analysis With Global and Local Moran's I

I ran the Global Moran's I again and created a correlogram for each study site using the GWR Model residuals (600 m – 1500 m distance lag) to determine a global autocorrelation trend. In addition I mapped the local spatial variability of the residuals using LISA, the local version of Moran's I (ESRI ArcGIS 9.3, 2008; Anselin 1995). The value derived for each polygon using this statistic included the standardized *z*-score ($\alpha = 0.05$ and 0.01) which was the interpreted value compared to the expected value (Wong and Lee 2005). These pattern analysis tools reported global and local Moran's I z scores using a 95% CI (±1.96 SD). Scores falling outside that range indicated a pattern that is not typically random (ESRI 2008). I computed the z-scores of the GWR model residuals using Local Moran's I to model the autocorrelation directionality for each study site and each year.

The local Moran statistic for areal unit ***i*** was defined as

$$I_i = z_i \sum_j w_{ij} \, z_j$$

where $\boldsymbol{z_i}$ and $\boldsymbol{z_j}$ were deviations from the mean for corresponding *x* values (Anselin 1995) (Figure 2).

RESULTS

Quantifying Landscape Fragmentation Trend over Time

Several of the 1963 historic photos did not have enough recognizable control points to match to the reference image or were within the 60% overlap and also were in steep terrain, so in these areas there was an offset ≤ 15 m. During the photo interpretation process, these areas were interpolated, based on surroundings. Figure 3 shows an example of an area where there were no control points in 1963 which would match subsequent photos.

Results of tests for sphericity and autocorrelation between *year* and *type* variables were highly significant for all three sites ($p < .0001$). Site 2 was the only site to show that there was a significant effect of *year* on variables *area_log* and *perim_log* for land use t*ypes urban* all years and *forest* in 1985 *($\alpha < .05$);* (Table 8). Across time, land cover classes *forest* and *agriculture* decreased in *area* and *urban* and *transportation* increased in *area* for all three sites. Since 1963, loss of *forest* and *agriculture* at study site 1 was 137 ha and loss at site 2 was 404 ha. Study site 3 lost 603 ha since 1977 (Figures 4-6).

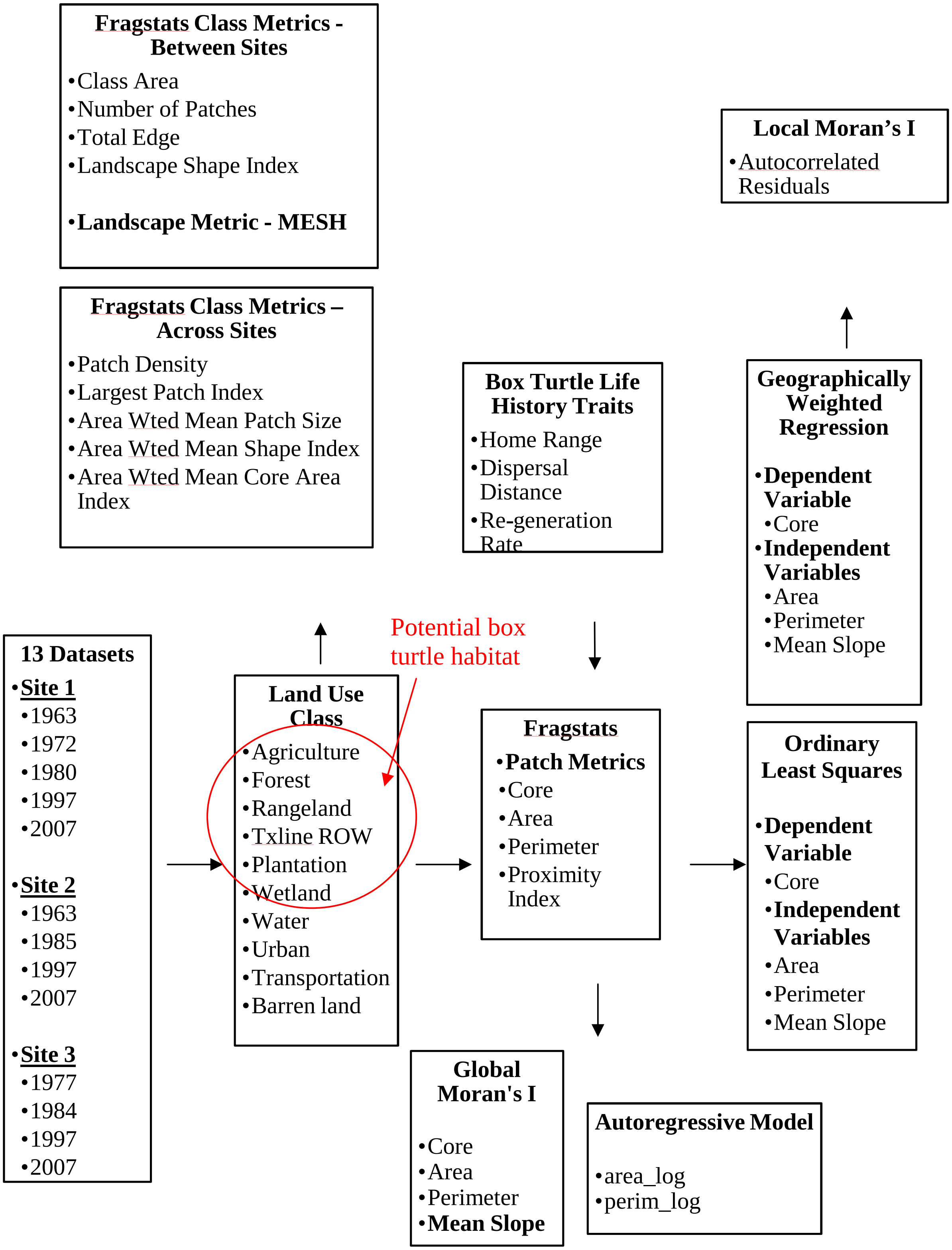


Figure 2. Flow chart of statistical applications and variables used.

Figure 3. Historic aerial photography with few recognizable features on the ground is prohibitive to placing matching control points to a reference image and will affect the accuracy of the ortho rectification process, particularly in rugged terrain. An example in study site 2 where it was not possible to place 6 to 9 evenly spaced control points in the frame. In 1963 (a) and 1985 (b) the northwest area of the image is steep slopes of contiguous forest without roads (or roads obscured by tree canopy) or other recognizable features. The 1997 (c) and 2007 (d) images of same location have road intersections that are easily identified between the two photos. Refer to Table 2 for sources of aerial photography.

Table 8. Site 2 results of SAS Proc mixed First Order Autoregressive Model for effect of year. Bold text denoted significance (alpha < 0.05). Of the 3 sites, site 2 was the only one to show that there was a significant effect of year on variables *area_log* and *perim_log* for *urban* all years and *forest* in 1985.

	Est.	SE	df	Pr >|t|	Est.	SE	df	Pr >|t|
Area log transformed (ha)								
	Ag				**Forest**			
	n =196				n= 263			
Intercept	4.3884	0.0899	55.0	**<.0001**	4.8361	0.0828	115.0	**<.0001**
1963	0.0000	0.1273	55.0	1.00	0.0000	0.1172	115.0	1.0000
1985	-0.1696	0.1503	55.0	0.2294	-0.3804	0.1130	115.0	**0.0010**
1997	-0.1642	0.1503	55.3	0.2794	-0.0348	0.1160	115.0	0.7648
2007	-0.1911	0.1558	55.8	0.2251	-0.0657	0.1155	115.0	0.5706
	Trans				**Urban**			
	n =63				n=565			
Intercept	3.7082	0.9134	1.5	0.0893	4.0570	0.0526	168.0	**<.0001**
1963	0.0000	1.2917	1.5	1.0000	0.0000	0.0744	168.0	**1.0000**
1985	-0.0707	1.2049	1.4	0.9605	0.3466	0.0762	169.0	**<.0001**
1997	-0.0613	1.2049	1.4	0.9658	0.3941	0.0768	169.0	**<.0001**
2007	-0.1144	1.1699	1.4	0.9345	0.3887	0.0761	168.0	**<.0001**

Perimeter log transformed (m)								
	Ag				**Forest**			
	n =196				n=263			
Intercept	3.0489	0.5515	56.8	**<.0001**	3.3285	0.0549	101.0	**<.0001**
1963	0.0000	0.0780	56.8	1.0000	0.0000	0.0776	101.0	1.0000
1985	-0.0986	0.0855	57.2	0.2539	-0.1988	0.0748	101.0	**0.0092**
1997	-0.0662	0.0922	57.6	0.4758	-0.0082	0.0768	101.0	0.9150
2007	-0.0888	0.0955	57.8	0.3564	-0.0269	0.0765	101.0	0.7259
	Trans				**Urban**			
	n =63				n=565			
Intercept	3.2333	0.6002	3.0	**0.0127**	2.8473	0.0343	175.0	**<.0001**
1963	0.0000	0.8488	3.0	1.0000	0.0000	0.0485	175.0	1.0000
1985	-0.1341	0.7827	2.8	0.8755	0.2336	0.0497	175.0	**<.0001**
1997	-0.1307	0.7827	2.8	0.8786	0.2565	0.0502	175.0	**<.0001**
2007	-0.1965	0.7578	2.8	0.8133	0.2515	0.0496	175.0	**<.0001**

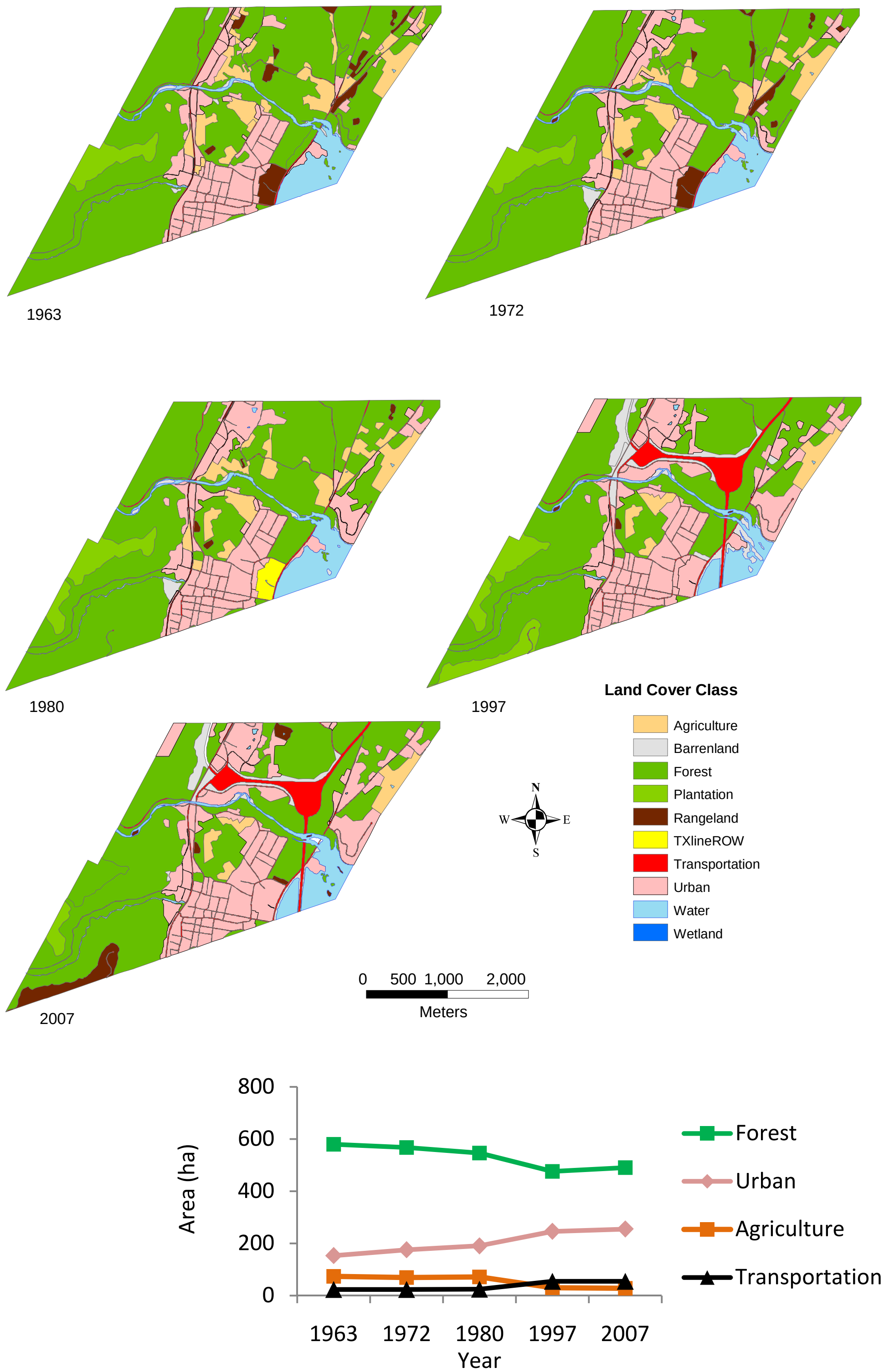
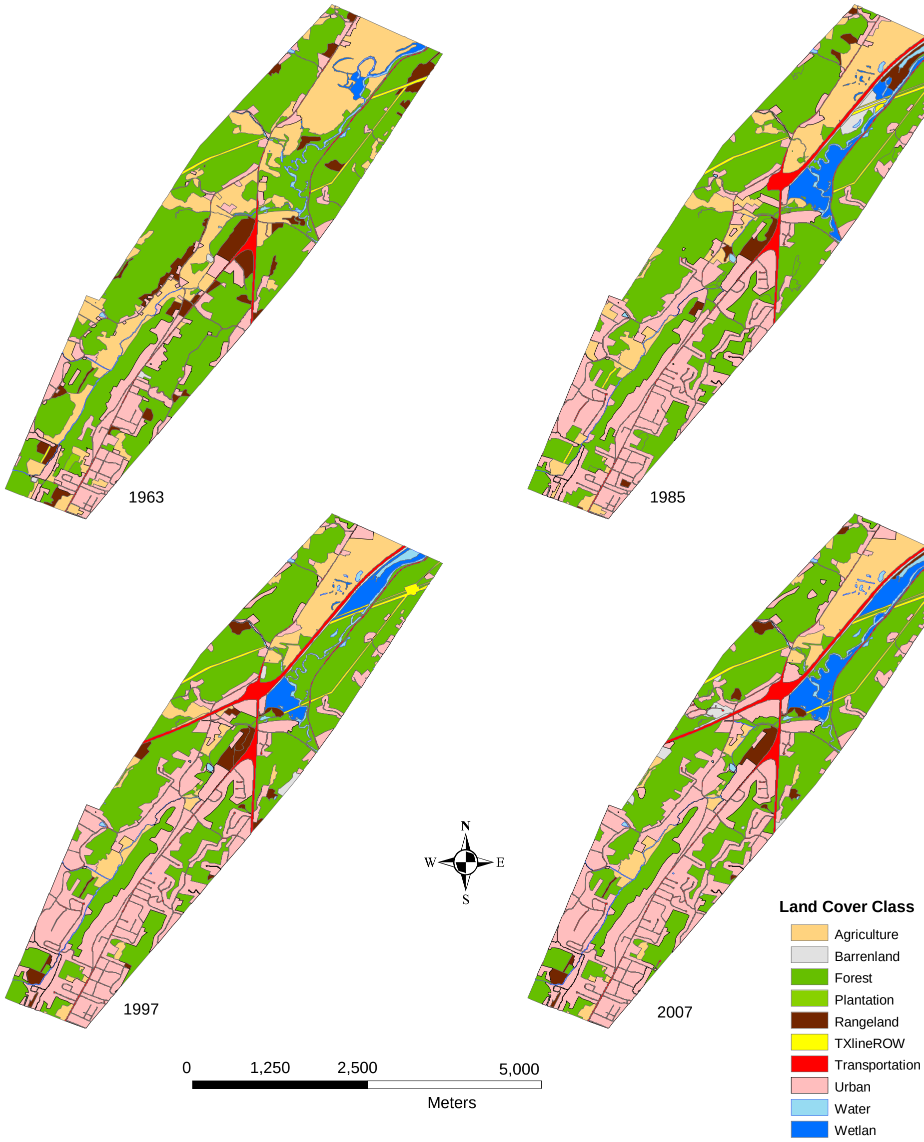


Figure 4. Results of photo interpretation of study site 1 land use land cover (LULC) classified with a modified Anderson Classification System. An imposing change in the 1997 landscape was the construction of Highway27 and the Highway 111 Interchange (red) in the 1980s. Graph shows the trend of change through time of forest, urban, agriculture and transportation area patches.



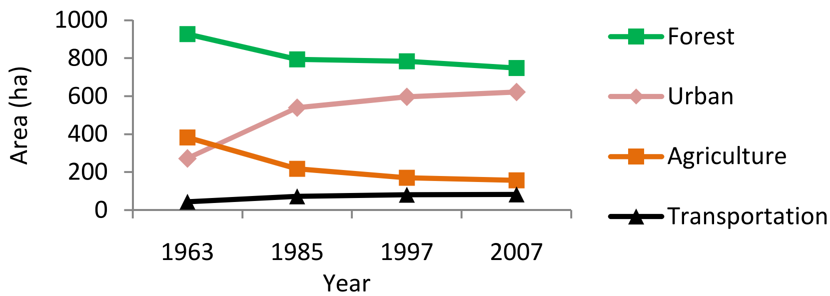


Figure 5. Results of photo interpretation of study site 2 land use land cover (LULC) classified with a modified Anderson Classification System. After 1963, the construction of the Highway 153/27 Interchange (red) corridor cut through the wetlands around Chickamauga creek. Urban (pink) classes increasingly replaced *agriculture* (orange) and *forest* (green) classes along the highway corridor.

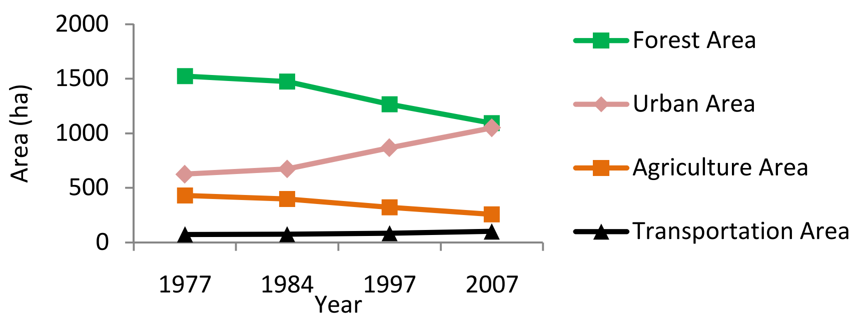


Figure 6. Results of photo interpretation of study site 3 land use land cover (LULC) classified with a modified Anderson Classification System. Between 1977 and 2007 the *urban* classes (pink) increasingly replaced the *agriculture* (orange) classes around Dallas Bay and the airport (the red rectangle in the lower southwest corner).

Fragmentation and Connectivity

Class level Fragstats metrics characterized fragmentation trends. *Patch density* and *mean patch size* were proxies for connectivity, fragmentation and dominance of *forest* in landscapes. I defined sites 2 and 3 as fragmented because each site showed a distinct trend of an increasing number of *forest* patches accompanied with smaller values for the *largest patch index, mean patch size, the area weighted mean patch size* and the *area weighted mean core area*. *Percent land* of forest and agriculture decreased in all three sites. The metric *total edge (m)* for *agriculture* decreased in all three sites and for *forest* at sites 1 and 2 (Table 9). Two unit less indices measuring average patch shape complexity were the *shape index* and *area weighted mean shape index*; the latter was more meaningful because it gave greater weight to larger polygons. Both indices increased at site 3, decreased at sites 1 and 2. The trend at site 3 of higher values of the *area weighted mean shape index* indicated that patch shapes were becoming more complex as they became fragmented. The number of *forest* patches in site 1 was fewer and the largest *forest* patch and *mean patch size* were getting smaller each decade but the mean *core* area was getting larger (Figure 7). The relationship of *forest* patches with *transportation* patches was significantly negative at site 2 and *forest* patches with *urban* patches at site 1 ($\alpha = 0.05$); (See Table 10 and Figures 8-1 & 8-2).

Rate of Core Forest Habitat Loss

Site 1 lost 4% of *core forest* habitat area per year between 1972 and 1980, but between 1997 and 2007 gained 2% per year. At this rate, it will be 117 years until all *core forest* habitat

Table 9. Fragstats class metrics. High patch density and low mean patch size suggested an urbanizing landscape (Weng 2007).

		Year	No. of patches	Mean patch size (ha)	Class Area (ha)	Percent Land	Patch density	Total edge (m)
Study Site 1	*Forest*	**1963**	35	16.6	579.6	61.5	3.7	79,512
		1972	33	17.2	567.1	60.1	3.5	73,975
		1980	32	17.1	545.9	57.9	3.4	76,225
		1997	26	18.3	475.4	50.4	2.8	69,594
		2007	27	18.1	489.7	52.1	2.9	68,132
	Agriculture	**1963**	23	3.2	74.1	7.9	2.4	25,027
		1972	16	4.3	69.0	7.3	1.7	19,750
		1980	20	3.6	71.8	7.6	2.1	21,685
		1997	6	4.9	29.4	3.1	0.6	6,469
		2007	6	4.6	27.5	2.9	0.6	6,337
	Transportation	**1963**	3	7.8	23.3	2.5	0.3	85,385
		1972	4	5.9	23.7	2.5	0.4	86,979
		1980	5	4.8	24.0	2.5	0.5	88,551
		1997	6	9.1	54.7	5.8	0.6	94,202
		2007	6	9.1	54.8	5.8	0.6	94,530
	Urban	**1963**	74	2.1	153.2	16.3	7.8	61,548
		1972	70	2.5	175.3	18.6	7.4	66,381
		1980	64	3.0	190.3	20.2	6.8	67,495
		1997	75	3.3	245.8	26.1	8.0	81,236
		2007	79	3.2	254.9	27.1	8.4	84,031
Study Site 2	*Forest*	**1963**	50	18.5	926.1	51.8	2.8	156,686
		1985	58	13.7	793.8	44.4	3.2	136,291
		1997	52	15.1	783.8	43.9	2.9	147,990
		2007	53	14.1	747.5	41.8	3.0	141,826
	Agriculture	**1963**	52	7.4	382.2	21.4	2.9	89,124
		1985	37	5.9	216.5	12.1	2.1	52,070
		1997	29	5.9	170.9	9.6	1.6	43,193
		2007	26	6.0	156.3	8.7	1.5	37,609
	Transportation	**1963**	13	32.2	43.6	2.4	0.7	118,201
		1985	18	59.4	72.5	4.1	1.0	146,683
		1997	18	67.3	80.5	4.5	1.0	153,846
		2007	21	66.6	81.9	4.6	1.2	157,692
	Urban	**1963**	121	6.5	272.3	15.2	6.8	111,620
		1985	110	13.8	539.0	30.2	6.2	183,049
		1997	107	16.6	596.3	33.4	6.0	193,347
		2007	111	16.8	621.1	34.8	6.2	196,831
Study Site 3	*Forest*	**1977**	141	10.8	1524.5	47.9	4.4	276,644
		1984	150	9.8	1472.7	46.3	4.7	291,646
		1997	148	8.5	1265.2	39.7	4.6	304,611
		2007	152	7.2	1093.4	34.4	4.8	286,293
	Agriculture	**1977**	113	18.3	429.7	13.5	3.6	132,890
		1984	119	17.5	397.6	12.5	3.7	131,676
		1997	111	15.2	320.2	10.1	3.5	114,883
		2007	92	9.6	257.9	8.1	2.9	98,005
	Transportation	**1977**	12	6.1	72.9	2.3	0.4	216,156
		1984	11	6.8	74.6	2.3	0.3	222,104
		1997	17	4.9	83.3	2.6	0.5	247,398
		2007	19	5.3	100.4	3.2	0.6	270,959
	Urban	**1977**	308	2.0	624.8	19.6	9.7	262,403
		1984	330	2.0	673.9	21.2	10.4	280,994
		1997	398	2.2	867.9	27.3	12.5	351,520
		2007	374	2.8	1050.1	33.0	11.7	392,471

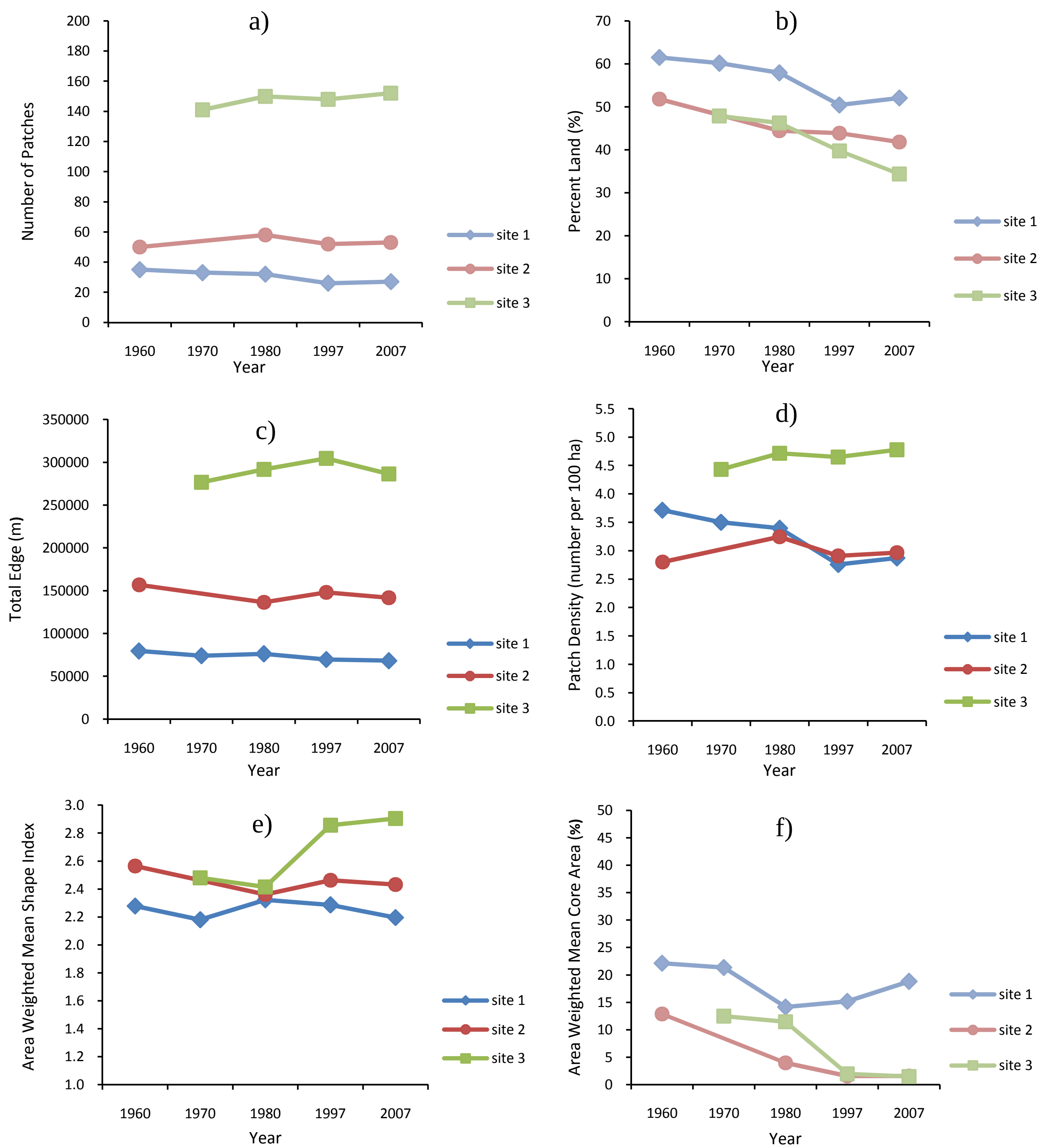


Figure 7. Fragstats class level metrics used to characterize *forest* fragmentation trends. (a) *number of patches*, (b) *percent land*, (c) *total edge*, (d) *patch density*, (e) *area weighted mean shape index*, (f) *area weighted mean core area*. Sites 2 and 3 were becoming more fragmented as demonstrated by the increase in number of *forest* patches, smaller values for the *area weighted mean core area (ha)* and increase in *forest patch density* (number of patches/100 ha). *Patch density* and *mean patch size* were proxies for connectivity, fragmentation and dominance of *forest* landscapes (Cho et al 2009). A unit less index measuring average patch shape complexity was the *area weighted mean shape index* which was more meaningful as weighted because it gave greater weight to larger polygons. This index increased in site 3, decreased in sites 1 and 2.

Table 10. Student's Paired t-Test Results of relationship between patches Forest – Urban, Forest – Transportation, Agriculture – Urban and Agriculture – Transportation. The forest – transportation relationship was significant for all 3 sites. Significance calculation adjusted after Bonferroni correction test ($\alpha \leq .0125$). See Figures 7-1 and 7-2.

Site	Student's Paired t-Test Probability Value, 1 tail	*df*	
	Forest - Urban		
1	0.00060	4	*
2	0.04130	3	
3	0.03622	3	
	Forest - Transportation		
1	0.00003	4	*
2	0.00029	3	*
3	0.00063	3	*
	Agriculture - Urban		
1	0.00390	4	
2	0.06399	3	
3	0.02234	3	
	Agriculture - Transportation		
1	0.18684	4	
2	0.03806	3	
3	0.00465	3	

* Significant at α .05

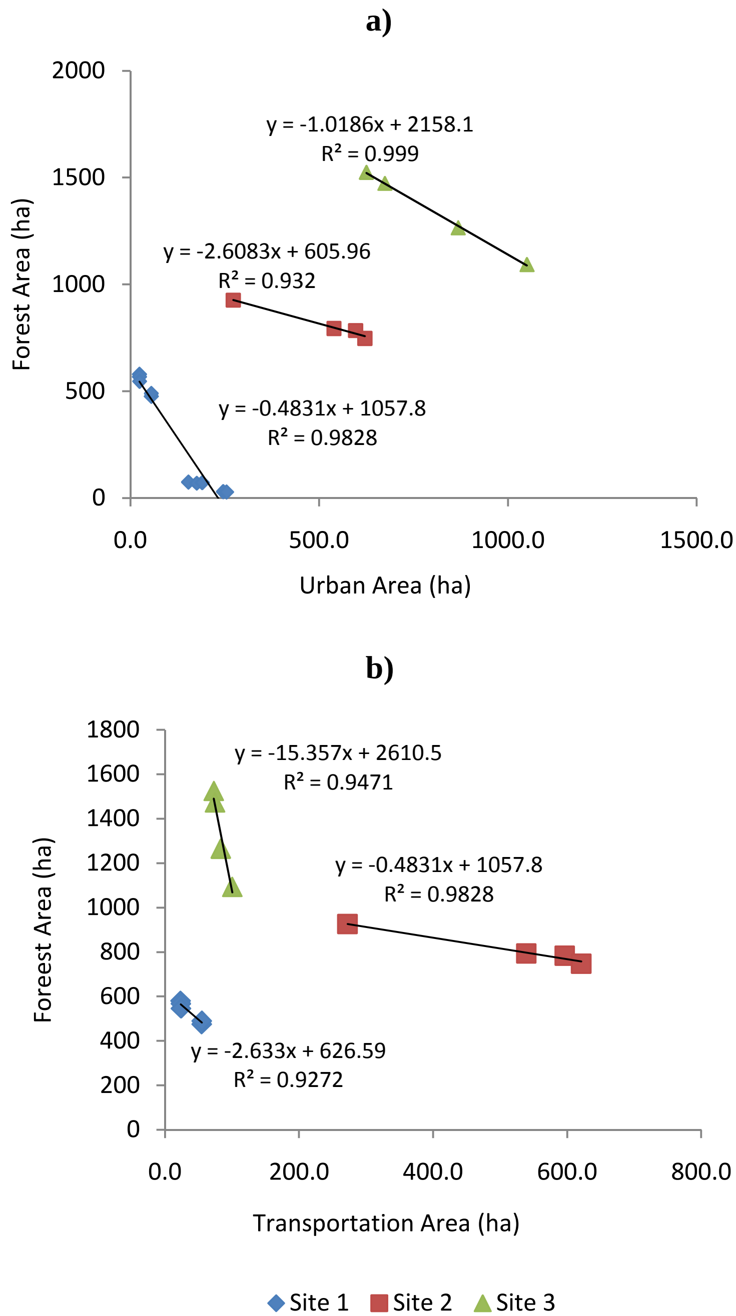


Figure 8-1 a-b. These regressions showed a negative relationship between *forest* and *urban* (a) and between *forest* and *transportation* (b). The regression line of site 1 in graph b) was short, suggesting that the sample duration was too small to capture the trend adequately.

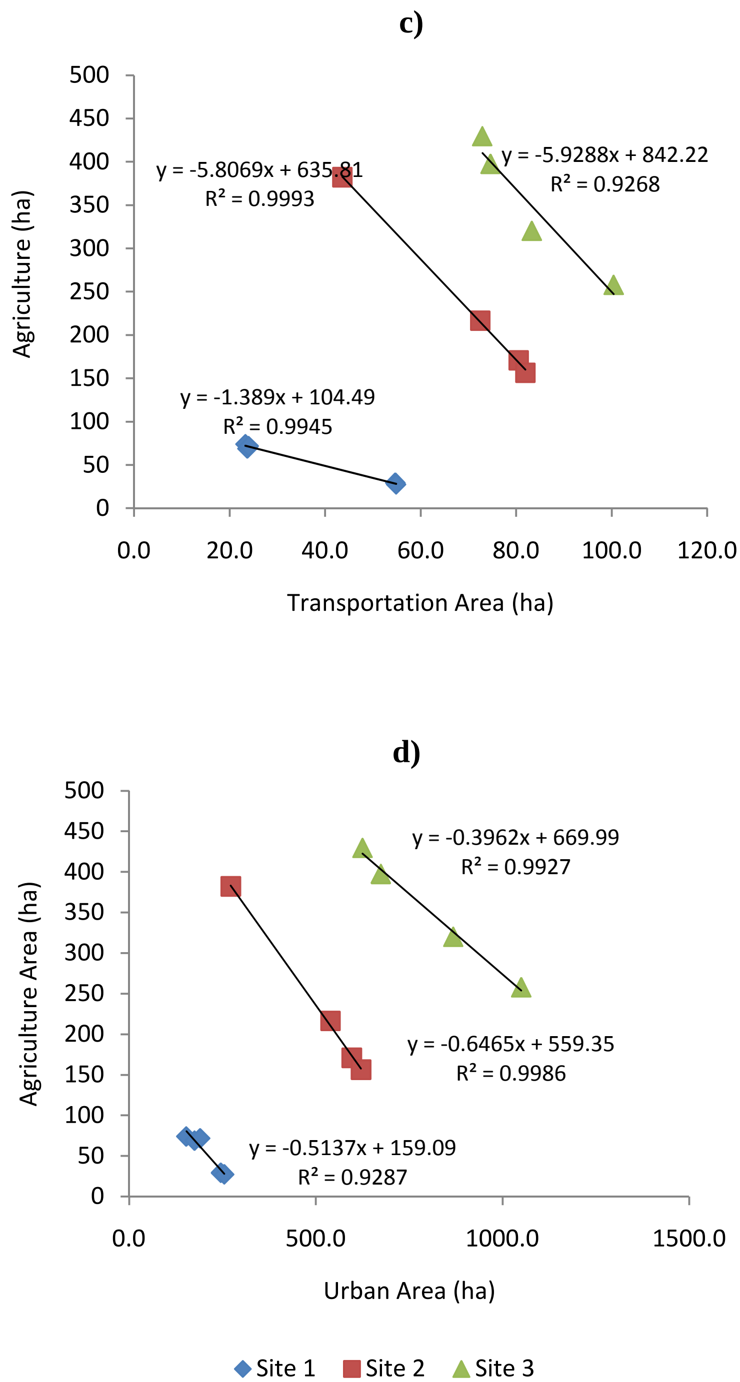


Figure 8-2 c-d. There was a negative relationship between *agriculture* and *transportation* (c) and between *agriculture* and *urban* (d). As an aside, these graphs were an excellent example of the relatively robust scaling relations of the *area* metric with respect to the three magnitudes of extent for each successive studysite 1, 2 and 3 (Wu 2004).

will be gone at site 1. Trends for sites 2 and 3 as shown in Table 11-1 indicated an increasing rate of loss of *core forest* habitat area over the years. Between 1997 and 2007 site 2 lost over 3% *core forest* habitat per year and in nine years all core forest habitat will be gone and rendered inhospitable for box turtles. Site 3 lost *core forest* habitat at 7.5% per year between 1997 and 2007, which was the highest rate of *core forest* habitat loss of all 3 sites and at this rate it will be gone in six years. Site 1 and 2 lost 52% and 83%, respectively, of total *core forest* habitat area since 1963 and site 3 lost 84% since 1977.

Rate of Core Box Turtle Habitat Loss and Re-generation Potential

All three sites had an overall decline in total area of *core* turtle habitat over the years (Figure 9). After 1963 site 1 and 2 lost 31% and 80% of *core* turtle habitat area, respectively, while site 3 lost 66% *core* turtle habitat after 1977. The *core* box turtle habitat maps showed the pattern of habitat fragmentation and eventual disappearance (Figure 10-12; Appendix E).

Site 1 rate of *core* habitat loss decreased from 1.40% per year between 1963 and 1972 to 0.02% per year between 1997 and 2007 and at this rate all will be gone in 110 years. Site 1 could sustain over three future generations of box turtles. The highest rate of *core* habitat area loss was at site 2 between 1997 and 2007 at 5.52% per year. In 11 years all *core* habitat will be gone at this rate. Rate of *core* habitat loss at site 3 has fluctuated. However, between 1997 and 2007 site 3 lost *core* habitat at 2.5% per year and at this rate it will be gone in 16 years. Site 2 and 3 could not sustain any future generations of box turtles, given the remaining *core* habitat and rate of habitat loss between 1997 and 2007 (Table 11-2).

Table 11-1. *Core* forest patch rate of change. The highest rate of *core* forest patch loss was at site 3 at 7.5% per year between 1997 and 2007.

Study Area	Year	Total area of core forest habitat (ha)	Number of years lapse	Interval	Total area of core forest habitat lost (ha)	Core forest habitat lost/yr (ha)	% Rate habitat loss/yr	Number of years until core forest habitat completely gone	Generations of box turtle until 0 core habitat left
1	1963	134.6							
1	1972	126.7	9	From 1963-1972	7.9	0.88	0.7%		
1	1980	86.83	8	From 1972-1980	39.87	4.98	3.9%		
1	1997	81	17	From 1980-1997	5.83	0.34	0.4%		
1	2007	97.7	10	From 1997-2007*	16.7	1.67	**	116.50	3.49
2	1963	235.1							
2	1985	65.8	22	From 1963-1985	169.3	7.70	3.3%		
2	1997	60.4	12	From 1985-1997	5.4	0.45	0.7%		
2	2007	41	10	From 1997-2007	19.4	1.94	3.2%	9.29	0.28
3	1977	182.3							
3	1984	184.9	7	From 1977-1984	2.6	0.37	0.2%		
3	1997	117.7	13	From 1984-1997	67.2	5.17	2.8%		
3	2007	29.5	10	From 1997-2007	88.2	8.82	7.5%	5.60	0.17

**2.1% c*ore forest* habitat gain

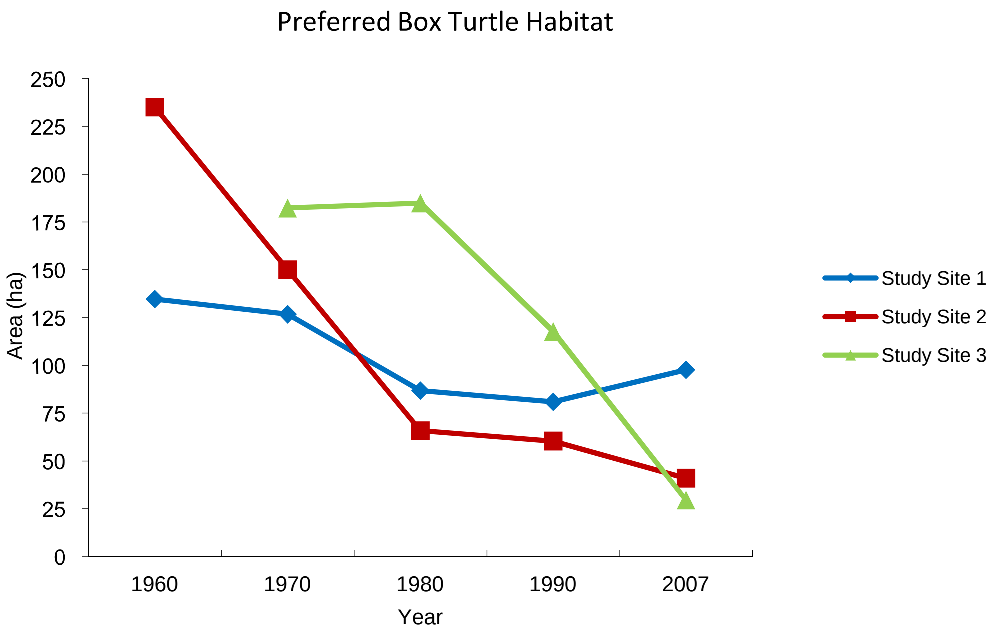


Figure 9. From 1963 to 2007, the eastern box turtle lost 52% and 82.5% of potential core habitat in site 1and 2, respectfully, and since 1977 site 3 lost 84% of potential habitat.

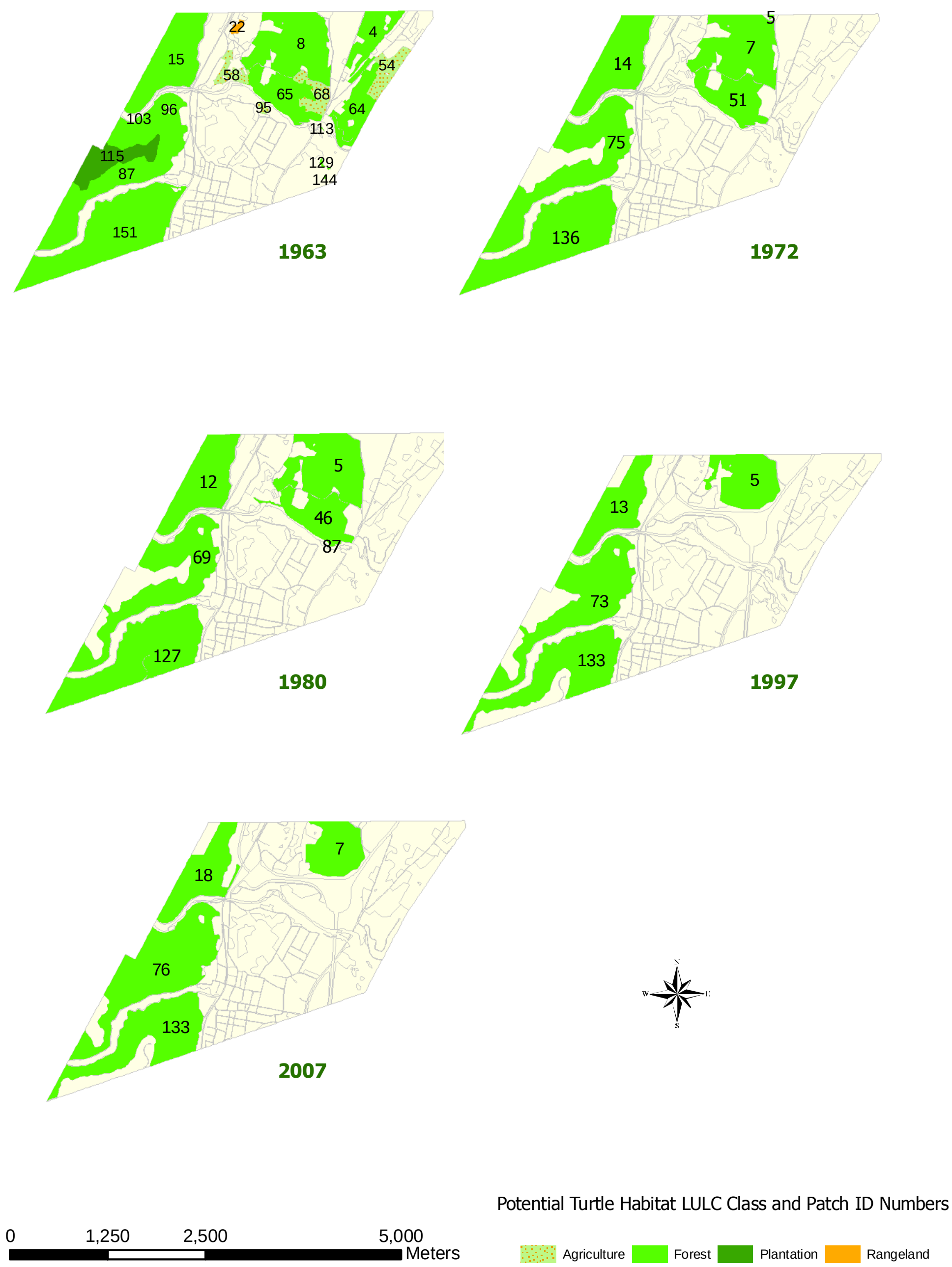


Figure 10. Potential eastern box turtle habitat patches were *forest, agriculture, rangeland, TXline ROW, plantation* and *wetland* LULC classes . *Core* habitat patches were ≥ 300 m distance from a contiguous *urban* or *transportation* patch and had a proximity of 300m from another potential habitat patch. Site 1 lost 52% *core* habitat area since 1963. The numbers in each potential habitat patch corresponded with the Patch ID (PID) number in Appendix E.

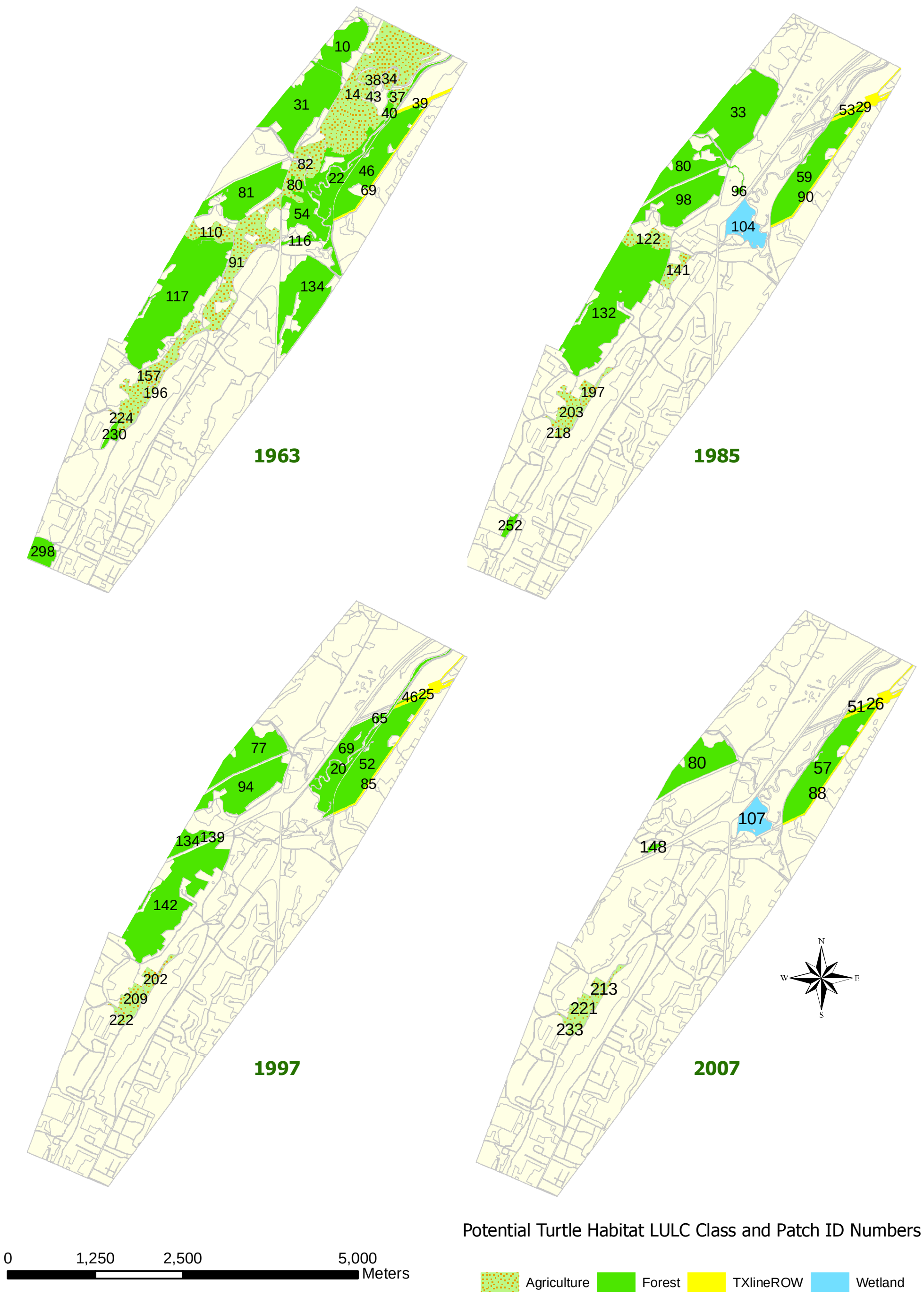


Figure 11. Study Site 2 lost 82.5% *core* habitat between 1963 and 2007. The potential habitat LULC classes that were the most vulnerable are *agriculture* and *forest*. The large agriculture patch in the northeast section in 1963 was dissected by the highway corridor in 1985, and lost *core* area.

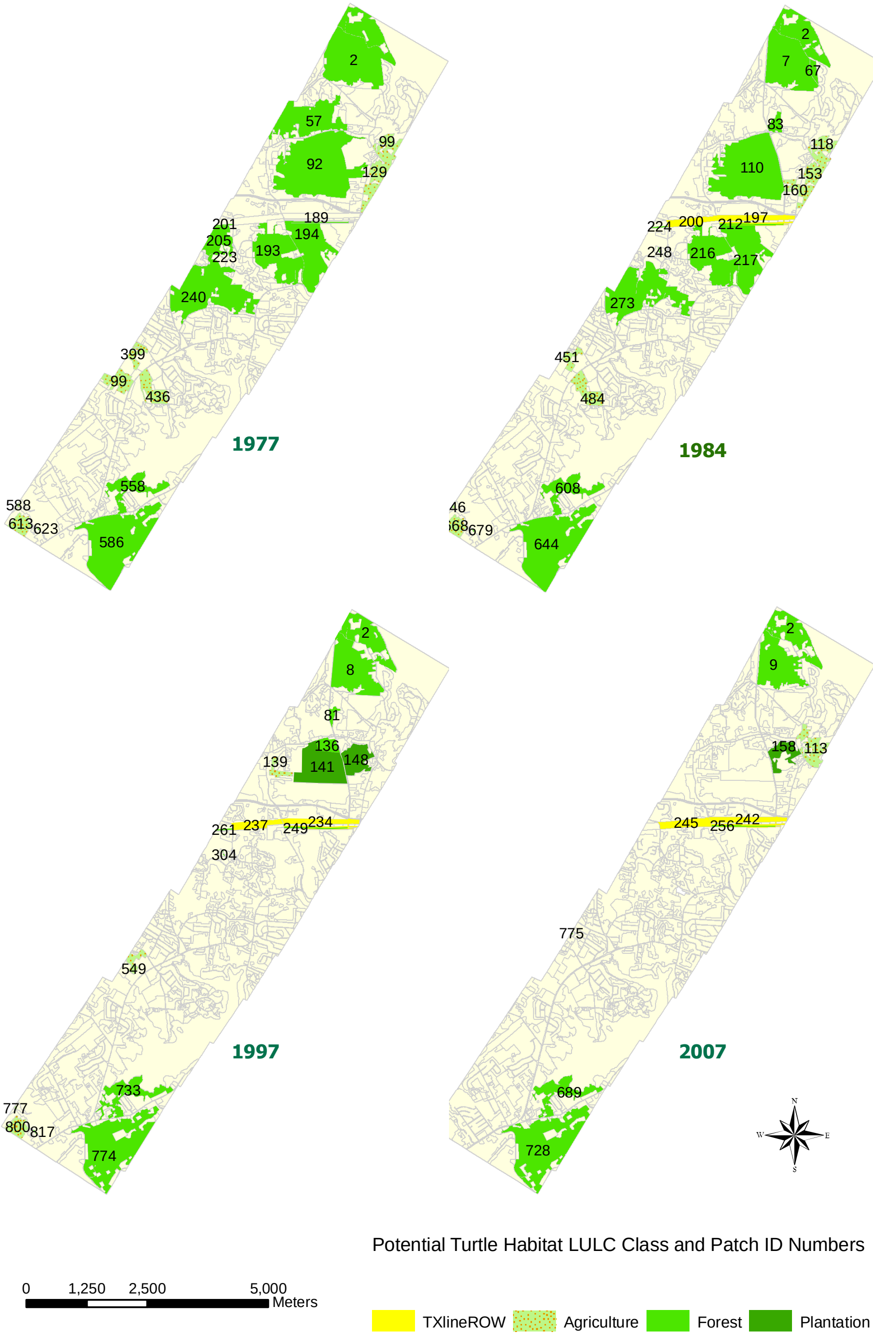


Figure 12. In 1977 site 3 had approximately 1,015 ha *core* habitat. The rate of habitat loss between 1977 and 1984 and 1984 and 1997 was 2.43% and 3.42 %, respectfully. In 2007 there was approximately 350 ha *core* habitat left. This site lost 7.5% of *core* habitat between 1997 and 2007, the highest rate of all 3 sites.

Table 11-2. *Core* area of potential box turtle habitat rate of change. Potential *core* LULC class types were defined as *forest, agriculture, transmission line right of way, plantation, wetland* and *range land.* The highest rate of *core* habitat loss was at site 2 at 5.52% per year between 1997 and 2007. The rate of change was faster than the box turtle can rebound. Site 1 lost 31% core habitat since 1963, site 2 lost 80% since 1963 and site 3 lost 66% since 1977.

Study Area	Year	Total area of core habitat (ha)	Number of years lapse	Interval	Total area of core habitat lost (ha)	habitat lost/yr (ha)	% Rate habitat loss/yr	Number of years until core habitat completely gone	Generations* of box turtle until 0 habitat left
1	1963	426.9							
1	1972	372.7	9	From 1963-1972	54.2	6.02	1.40%		
1	1980	363.73	8	From 1972-1980	8.97	1.12	0.03%		
1	1997	301.1	17	From 1980-1997	62.63	3.68	0.13%		
1	2007	293.2	10	From 1997-2007	7.9	0.79	0.02%	109.42	3.28
2	1963	724.6							
2	1985	405.6	22	From 1963-1985	319	14.50	2.00%		
2	1997	317.8	12	From 1985-1997	87.8	7.32	1.80%		
2	2007	142.4	10	From 1997-2007	175.4	17.54	5.52%	10.76	0.32
3	1977	1015.6							
3	1984	843	7	From 1977-1984	172.6	24.66	2.43%		
3	1997	468.7	13	From 1984-1997	374.3	28.79	3.42%		
3	2007	349.8	10	From 1997-2007	118.9	11.89	2.54%	15.76	0.47

*Congdon et al. (1993) cohort generation time for Blandings turtle = 37.5 yrs. (rate as .03/yr). Cohort generation time was the average length of time between birth of an individual and birth of its own offspring .

Mesh Landscape Metric

The *mesh* landscape level metric was a proxy for characterizing road density in the matrix. The lower limit of the *mesh* metric was achieved when the landscape was maximally subdivided. The *mesh* metric was the same as the area-weighted mean patch size where the proportional area of each patch was based on total landscape area. The most dramatic change in average *mesh* size was in study site 3 which went from 61.8 ha in 1977 to 43 ha in 2007, the average patch was reduced by 19 ha. Since 1963, the mean patch size at site 1 lost 6 ha and site 2 lost 9 ha. The trend for all three study sites was toward increased fragmentation (Figure 13).

Exploratory Spatial Statistics

I mapped spatial distribution over time of the variables *core* (column 1), *area* (column 2), *perim* (column 3) and *mean_slope* (column 4) (Figures 14-1 - 3). Spatial distribution of *mean_slope* values at sites 1 and 3 did not vary over the years. This trend was reflected in the Global Moran's I correlograms for *mean_slope* which indicated that this variable was highly autocorrelated all years and distances, except for site 2 where there were no significant values at distance classes 1200 m and 1500 m (Figures 15-1 - 3). Site 2 variation in *mean_slope* was attributed to the dissection of polygons over time which modified the mean slope values. The variables *area* and *perim* showed little autocorrelation at all three sites. Site 2 was not significant for *core* in all years except in 1963 at 1500 m. This trend was shown in Figure 14-2 column 1 by the clumped areas with reduced *core* values increasing over time. Sites 1 and 3 did not have extensive significant autocorrelation values for *core.*

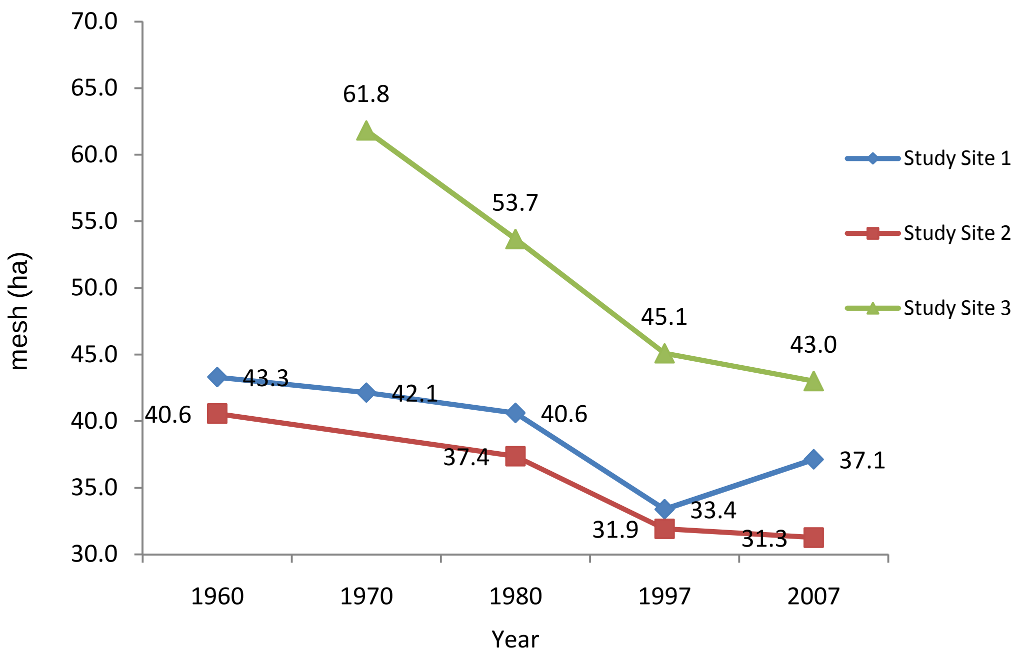


Figure 13. Maximum value of *mesh* (hectares) was when the landscape consisted of a single patch. Lower limit was achieved when the landscape was maximally subdivided; when every cell was a separate patch (Forman et al. 2003). Values represented area weighted mean patch size, where the proportional area of each patch was based on total landscape (McGarigal and Marks 1994).

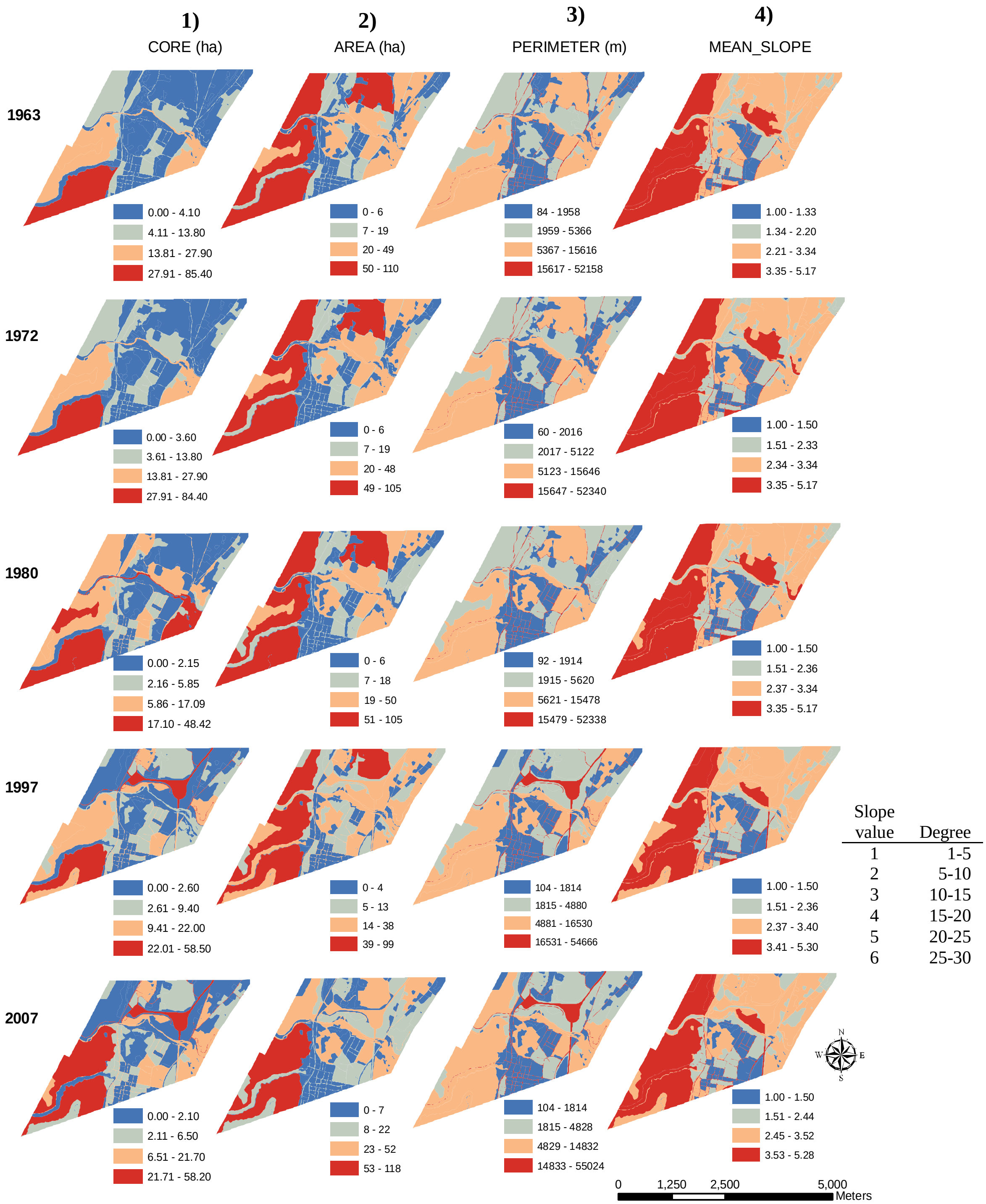


Figure 14-1. Site 1 – Quantitative spatial distribution of variables *core (ha), area (ha), perimeter (m)* and *mean slope* (unitless – refer to Table for conversion to degree interval). The spatial analysis "switched gears" and focused on core patch area fragmented over time as a function of the area, perimeter and mean slope of the patch. Land use class was not considered but the size and configuration of patches as they changed through time.

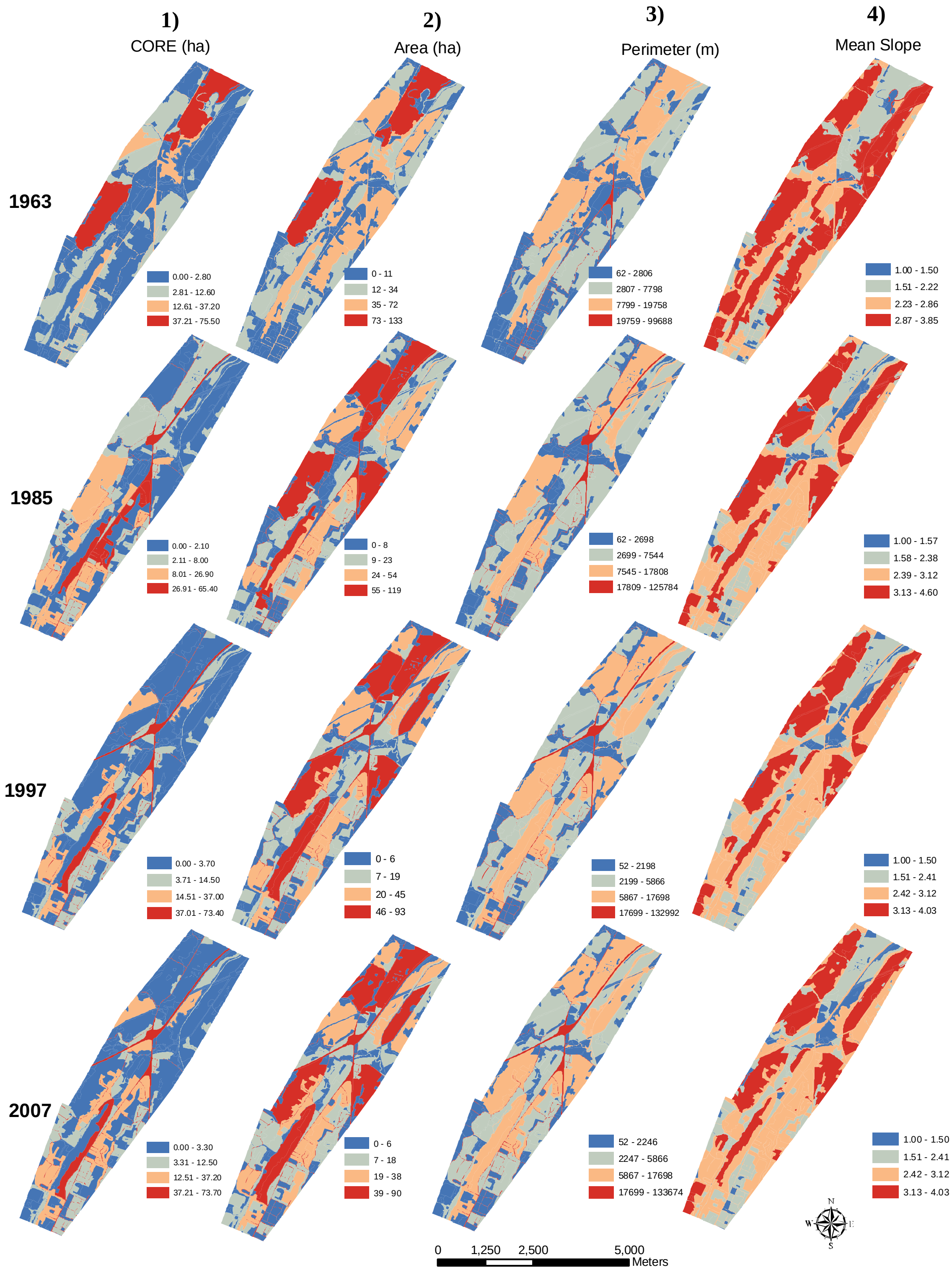


Figure 14-2. Site 2 – Quantitative spatial distribution of variables *core*, *area*, *perimeter* and *mean slope*.

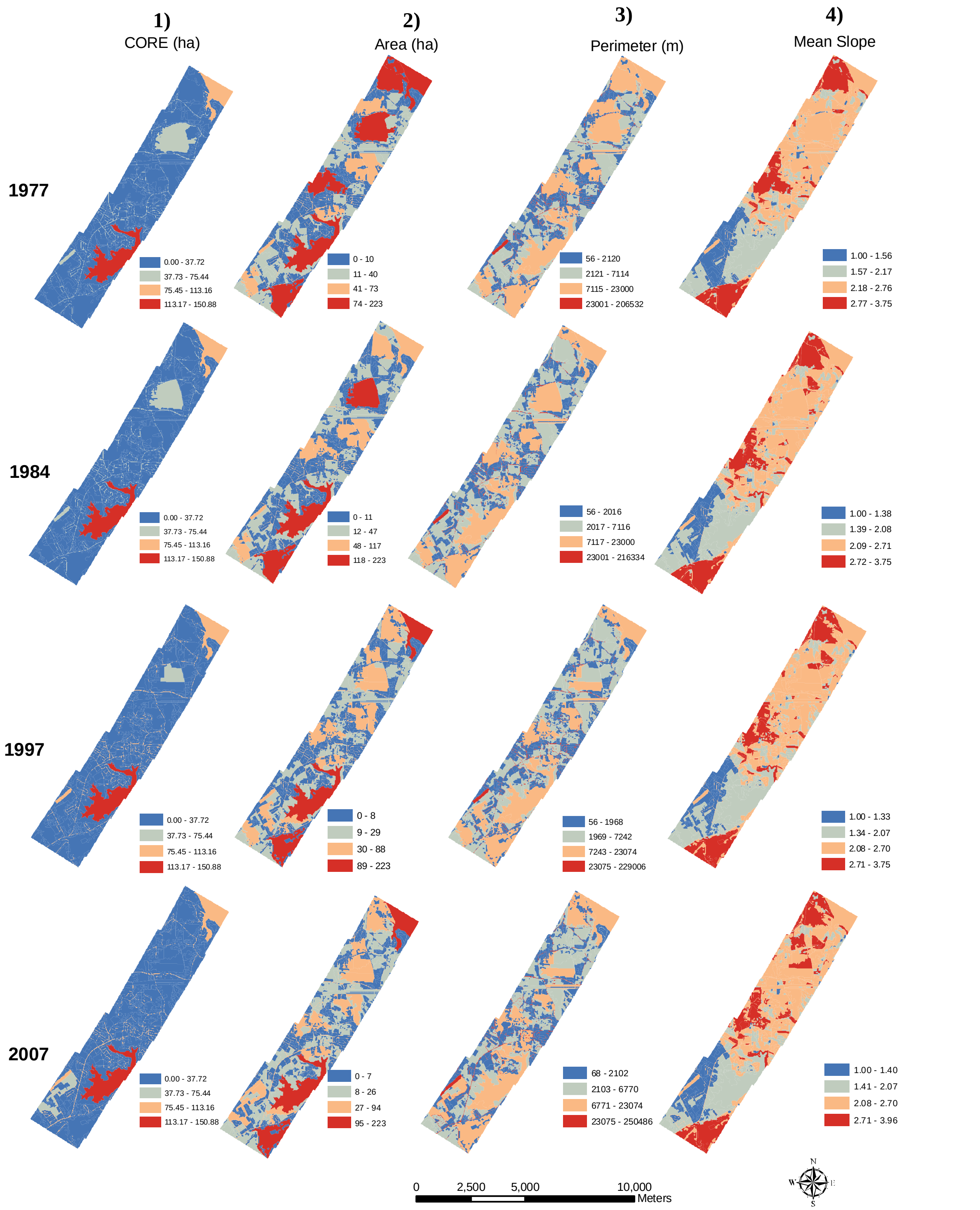


Figure 14-3. Site 3 – Quantitative spatial distribution of variables *core, area, perimeter* and *mean slope*.

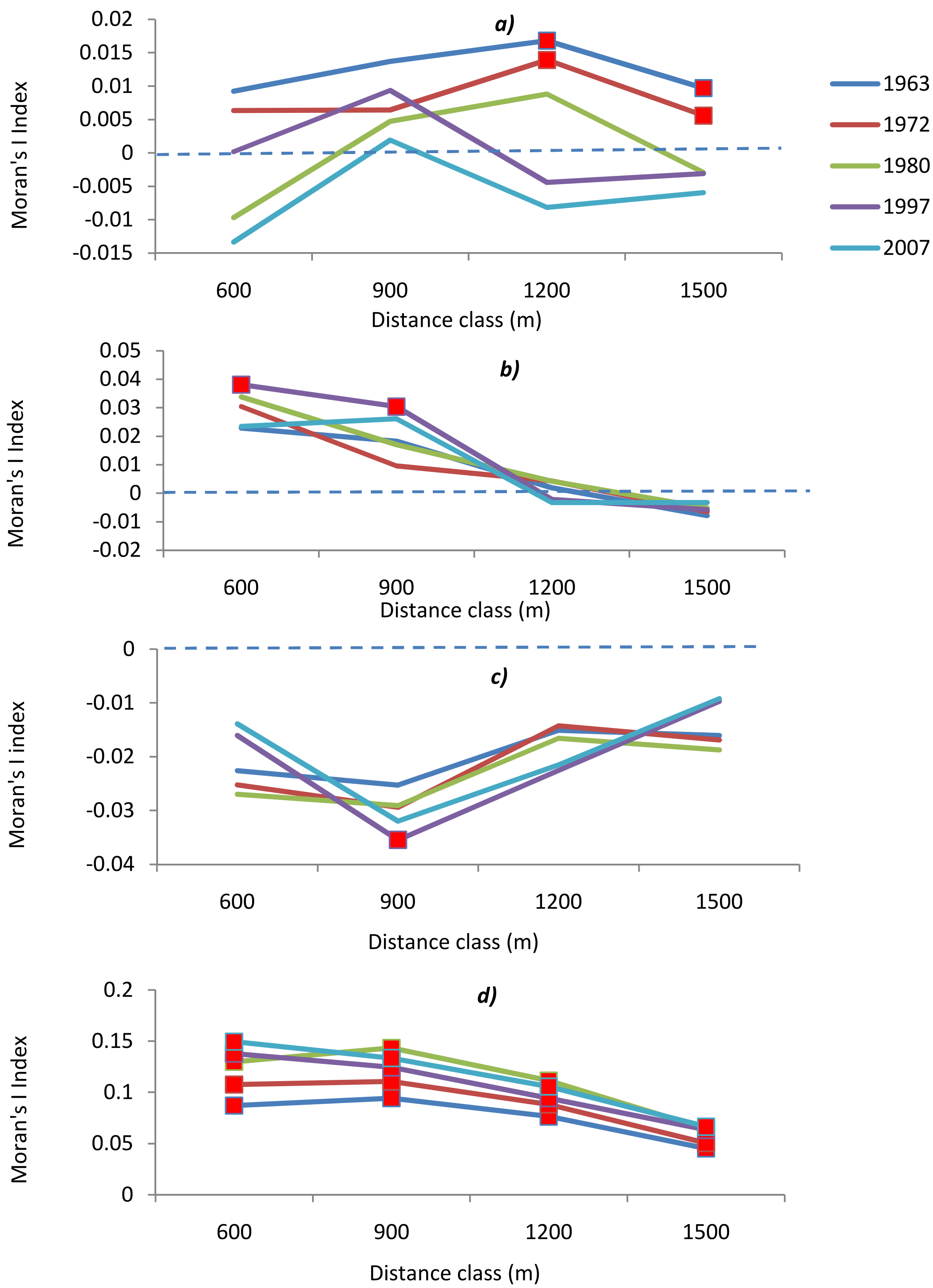


Figure 15-1. Site 1 Global Moran's I correlogram of each model variable. I used a correlogram to graph a trend with the distance class on the x axis and the statistic coefficient on the y axis. Global Moran's I Coefficient was a standardized value based on procedure, not an ad hoc classification; positive autocorrelation values ranged from 0 ≥ to 1, negative values ranged from 0 to ≥ -1. **(a)** *core* - significant values at 1200 and 1500 m were in 1963 and 1972. **(b)** *area* - significant values at 600 and 900 m in 1997.**(c)** *perim* - one significant value at 900 m in 1997. **(d)** *mean_slope* - significant all years and distance classes. Red symbols indicated significant Moran's I values at $p \leq 0.05$.

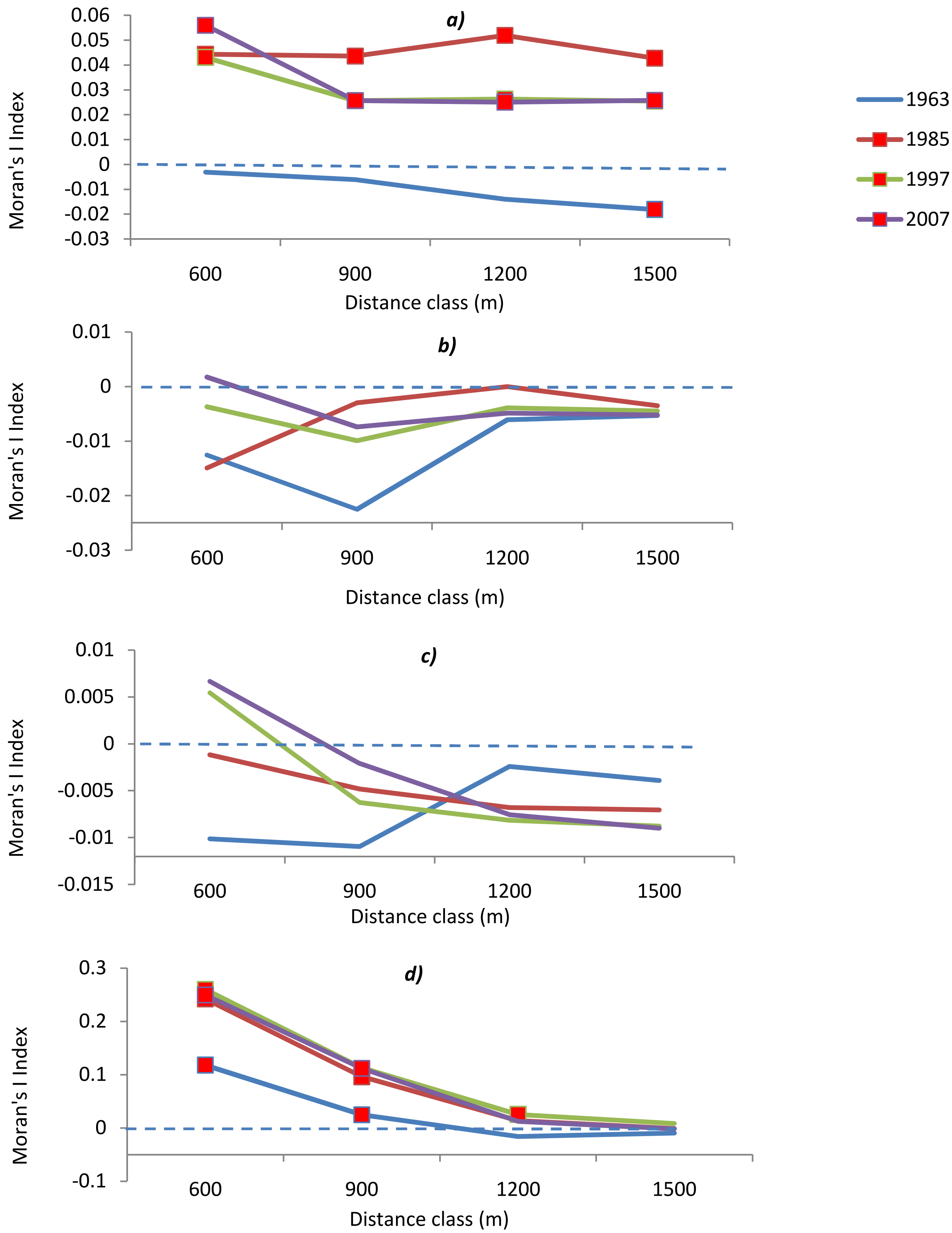


Figure 15-2. Site 2 Global Moran's I correlogram of each model variable. **(a)** *core*, **(b)** *area*, **(c)** *perim* and **(d)** *mean_slope* . No significant values for *area* and *perim*. Red symbols indicated significant Moran's I values at $p \leq 0.05$. *Mean_slope* was significant all years at 600 m and 900 m and at 1200 m in 1997. The Global Moran's I coefficient demonstrated that as the distance increases, the lines attenuate to 0 indicating the pattern becomes more random.

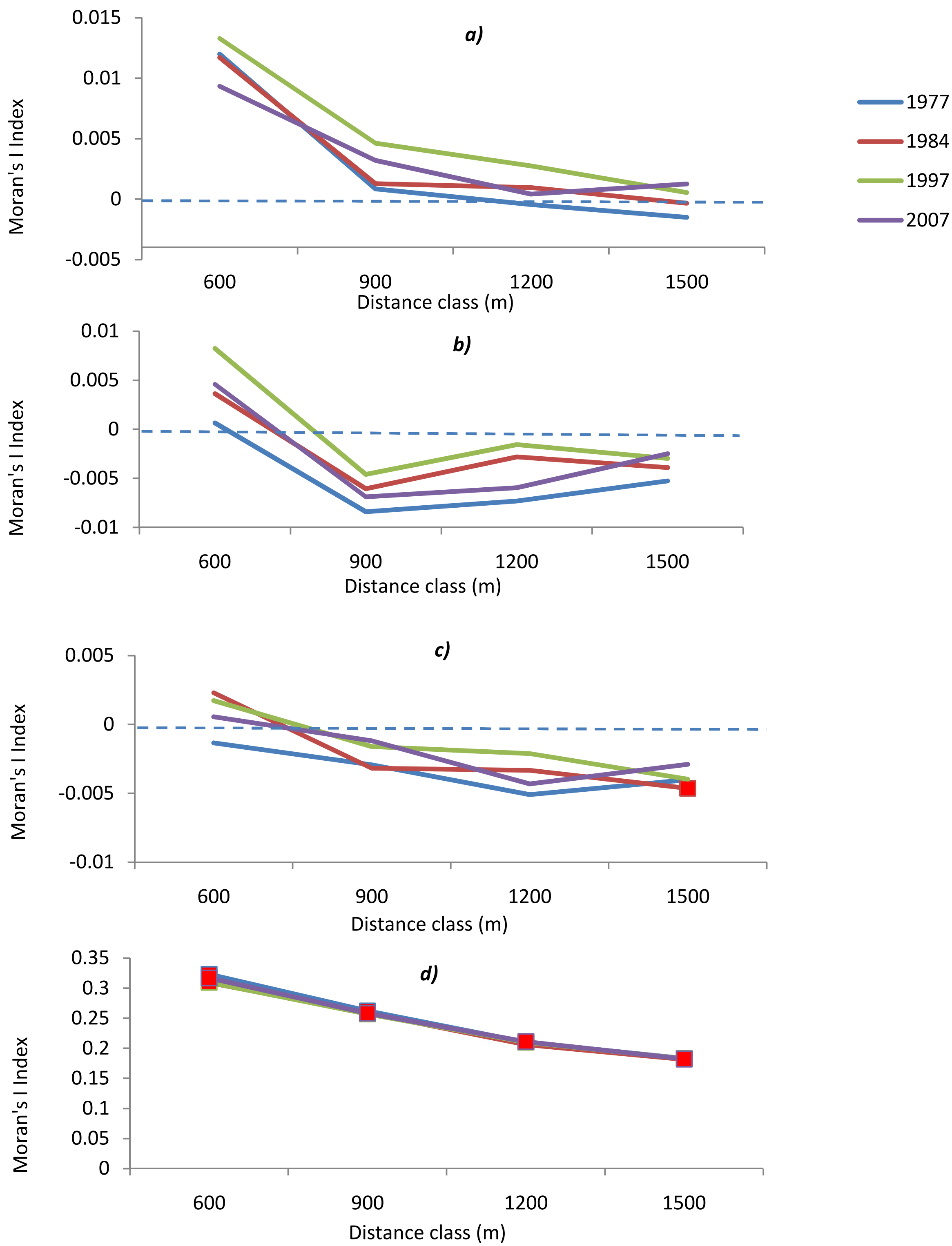


Figure 15-3. Site 3 Global Moran's I correlogram of each model variable. **(a)** *core*, (**b**) *area*, **(c)** *perim* and **(d)** *mean_slope*. Red symbols indicated significant Moran's I values at $p \leq 0.05$. *Area* and *core* did not have any significant autocorrelation values and *perim* had one significant value at 1500m in 1984. M*ean slope* was significantly autocorrelated at all distance classes and years.

Global OLS Regression

Significant results of the Joint Wald Statistic indicated robust overall model significance. The Jarque-Bera statistic indicated that residuals deviated from a normal distribution. Koenker Statistic had significant results indicating biased standard errors, so I reported the Robust probability estimates which include:

Model A (*area*)

Core had a significant positive relationship with *area* at all sites and years ($p < .05$).

Model B (*area, perim*)

Core did not have a significant relationship with *area* at site 2 in 1985 and 1997 or at site 3 in 2007.
Perimeter was not significant at site 1 in 1963 and 1972.

Model C (*area, perim, mean_slope*)

Core did not have a significant relationship with *area* at site 2 in 1985, 1997 and 2007.
Perimeter was not significant at site 1 in 1963 and 1972.
Mean slope had a significant negative relationship with *core* at site 3 for all years and at site 2 in 1972.
Mean slope was not significant at site 1 any years or site 2 in 1985 and 1997.

(But see Table 12)

Model Comparison and Selection

All GWR Models had lower AIC_c scores and higher R^2 values than the OLS model which indicated that GWR was a better fit of the data. The constant global values of the OLS Model under estimated coefficients compared to the range of GWR model estimates (Table 13). For reasons of consistency and ecological interest with the *mean_slope* variable, I chose model C for further regression analysis.

Table 12. OLS Statistics Model C. Asterisk denoted significant Robust Probability values ($p \leq .05$). For each patch (polygon) this model showed the dependency of *core* area with the area (*area (ha)*), perimeter *(perim (m))* and mean slope *(mean slope)* of that polygon.

Dataset	Site	Variable	Coef (β)	StdError	t_Stat	Prob	Robust_SE	Robust_t	Robust_Pr	
1963_1	1	Area	0.3844	0.0335	11.4855	0.0000	0.1670	2.3020	0.0227	*
1963_1	1	Intercept	0.7880	1.1018	0.7151	0.4756	0.9014	0.8741	0.3834	
1963_1	1	Mean_slope	-0.5035	0.5729	-0.8789	0.3808	0.6421	-0.7842	0.4341	
1963_1	1	Perim	0.0001	0.0001	1.4826	0.1402	0.0001	1.4879	0.1388	
1972_1	1	Area	0.3691	0.0364	10.1395	0.0000	0.1715	2.1520	0.0331	*
1972_1	1	Intercept	0.4951	1.2154	0.4073	0.6844	0.9348	0.5296	0.5972	
1972_1	1	Mean_slope	-0.2585	0.6207	-0.4164	0.6777	0.6430	-0.4020	0.6883	
1972_1	1	Perim	0.0001	0.0001	1.3482	0.1797	0.0001	1.4293	0.1551	
1980_1	1	Area	0.2488	0.0277	8.9950	0.0000	0.0913	2.7263	0.0072	*
1980_1	1	Intercept	0.3866	0.8911	0.4338	0.6651	0.7839	0.4931	0.6227	
1980_1	1	Mean_slope	0.1033	0.4557	0.2266	0.8210	0.5251	0.1967	0.8443	
1980_1	1	Perim	0.0002	0.0001	2.7160	0.0075	0.0000	4.2511	0.00001	*
1997_1	1	Area	0.3141	0.0379	8.2891	0.0000	0.1294	2.4283	0.0164	*
1997_1	1	Intercept	1.4814	1.0345	1.4319	0.1544	0.9130	1.6226	0.1069	
1997_1	1	Mean_slope	-0.5794	0.5213	-1.1114	0.2683	0.5606	-1.0336	0.3031	
1997_1	1	Perim	0.0003	0.0001	4.1949	0.0001	0.0002	2.1001	0.0375	*
2007_1	1	Area	0.3453	0.0318	10.8503	0.0000	0.0959	3.6007	0.0004	*
2007_1	1	Intercept	1.7287	0.9297	1.8595	0.0650	0.8631	2.0030	0.0470	*
2007_1	1	Mean_slope	-0.7797	0.4583	-1.7013	0.0910	0.4759	-1.6383	0.1035	
2007_1	1	Perim	0.0003	0.0001	4.6377	0.0000	0.0001	2.2922	0.0233	*
1963_2	2	Area	0.3368	0.0222	15.1871	0.0000	0.1074	3.1361	0.0019	*
1963_2	2	Intercept	2.4156	0.9299	2.5978	0.0099	0.8551	2.8249	0.0051	*
1963_2	2	Mean_slope	-1.2162	0.4141	-2.9366	0.0036	0.4942	-2.4608	0.0144	*
1963_2	2	Perim	0.0002	0.0000	4.2270	0.0000	0.0001	3.0423	0.0026	*
1985_2	2	Area	0.0719	0.0230	3.1259	0.0020	0.0498	1.4430	0.1502	
1985_2	2	Intercept	0.4230	0.8252	0.5126	0.6087	0.4819	0.8777	0.3809	
1985_2	2	Mean_slope	0.2873	0.3720	0.7724	0.4405	0.2762	1.0404	0.2991	
1985_2	2	Perim	0.0005	0.0000	12.1722	0.0000	0.0000	17.8912	0.00001	*
1997_2	2	Area	0.0963	0.0299	3.2219	0.0014	0.0822	1.1716	0.2424	
1997_2	2	Intercept	0.9392	0.9429	0.9961	0.3201	0.5559	1.6896	0.0923	
1997_2	2	Mean_slope	0.0008	0.4199	0.0018	0.9985	0.3112	0.0025	0.9980	
1997_2	2	Perim	0.0005	0.0000	11.6128	0.0000	0.0000	10.8828	0.00001	*
2007_2	2	Area	0.1151	0.0303	3.7988	0.0002	0.0893	1.2880	0.1988	
2007_2	2	Intercept	1.0786	0.9291	1.1609	0.2467	0.5631	1.9156	0.0564	*
2007_2	2	Perim	0.0005	0.0000	11.3099	0.0000	0.0000	9.9826	0.00001	*
2007_2	2	Mean_slope	-0.0915	0.4140	-0.2210	0.8252	0.3178	-0.2879	0.7736	
1977_3	3	Area	0.3475	0.0125	27.8581	0.0000	0.1058	3.2838	0.0011	*
1977_3	3	Intercept	1.4870	0.6482	2.2939	0.0221	0.5078	2.9282	0.0035	*
1977_3	3	Mean_slope	-0.8020	0.3181	-2.5213	0.0119	0.3611	-2.2208	0.0267	*
1977_3	3	Perim	0.0002	0.0000	8.9782	0.0000	0.0000	6.3347	0.00001	*
1984_3	3	Area	0.4001	0.0121	32.9272	0.0000	0.1043	3.8354	0.0001	*
1984_3	3	Intercept	1.3949	0.5532	2.5217	0.0119	0.4478	3.1148	0.0019	*
1984_3	3	Mean_slope	-0.8450	0.2726	-3.1001	0.0020	0.3226	-2.6195	0.0090	*
1984_3	3	Perim	0.0002	0.0000	9.2533	0.0000	0.0000	5.6599	0.00001	*
1997_3	3	Area	0.4123	0.0141	29.2310	0.0000	0.1282	3.2152	0.0014	*
1997_3	3	Intercept	1.4061	0.5412	2.5980	0.0095	0.4549	3.0911	0.0021	*
1997_3	3	Mean_slope	-0.7962	0.2672	-2.9804	0.0030	0.3198	-2.4895	0.0130	*
1997_3	3	Perim	0.0002	0.0000	8.4263	0.0000	0.0001	3.5712	0.0004	*
2007_3	3	Area	0.4415	0.0151	29.3160	0.0000	0.1272	3.4699	0.0006	*
2007_3	3	Intercept	1.4677	0.5741	2.5564	0.0108	0.5236	2.8029	0.0052	*
2007_3	3	Mean_slope	-0.8321	0.2803	-2.9687	0.0031	0.3275	-2.5410	0.0112	*
2007_3	3	Perim	0.0002	0.0000	9.7743	0.0000	0.0001	3.8369	0.0001	*

Table 13. Comparison of OLS and GWR model fitting statistics, corrected Akaike Information Criterion (AICc) and coefficient of determination (**R^2**). * denoted lowest AICc Score. I used model C because I wanted to investigate the dependency of *core* with *mean slope*. ** Number of significantly autocorrelated polygons reported from Local Moran's I statistic of GWR Model residuals at 600 m bandwidth (α ≤ .05).

Site	Dataset	Model	OLS AICc	OLS R^2 Adjusted	GWR Neighbors (Adaptive)	GWR AICc		GWR R^2 Adjusted	No. of Sig. z**
1	1963	A	970.220	0.557	18	796.927	*	0.893	4
		B	970.438	0.554	39	803.132		0.867	5
		C	971.647	0.553	37	811.125		0.873	4
	1972	A	922.309	0.514	21	767.682		0.871	5
		B	922.610	0.516	42	766.609	*	0.854	6
		C	924.432	0.513	42	776.352		0.854	5
	1980	A	797.904	0.503	40	740.146		0.708	9
		B	791.909	0.527	44	721.619	*	0.749	5
		C	793.85	0.524	40	726.674		0.762	5
	1997	A	888.55	0.459	19	754.403		0.845	8
		B	874.45	0.512	28	704.279	*	0.883	6
		C	875.191	0.513	28	731.867		0.876	6
	2007	A	893.194	0.548	18	763.291	*	0.867	9
		B	876.519	0.598	25	707.609		0.905	6
		C	875.575	0.603	30	760.758		0.871	5
2	1963	A	1783.574	0.513	13	1412.210	*	0.919	15
		B	1768.915	0.538	19	1458.040		0.900	12
		C	1762.300	0.550	33	1540.240		0.838	10
	1985	A	1684.933	0.203	22	1492.046		0.692	9
		B	1568.074	0.488	31	1435.538	*	0.748	8
		C	1569.469	0.487	31	1468.968		0.743	8
	1997	A	1764.515	0.224	26	1589.602		0.661	9
		B	1655.477	0.484	32	1548.061	*	0.716	8
		C	1657.477	0.482	31	1548.823		0.747	11
	2007	A	1829.703	0.241	19	1638.776		0.709	12
		B	1724.535	0.480	26	1588.348	*	0.760	10
		C	1726.485	0.478	32	1610.730		0.744	11
3	1977	A	3895.797	0.603	17	2474.038	*	0.971	23
		B	3822.770	0.647	42	2739.692		0.945	12
		C	3818.405	0.649	60	2944.129		0.923	13
	1984	A	4102.009	0.655	19	2718.334	*	0.965	25
		B	4024.716	0.692	45	2842.869		0.952	22
		C	4017.117	0.696	65	3014.563		0.937	23
	1997	A	4743.495	0.587	18	3305.227	*	0.952	22
		B	4678.371	0.620	74	3546.255		0.916	19
		C	4671.493	0.624	74	3572.617		0.916	21
	2007	A	4503.120	0.617	19	3277.395	*	0.945	22
		B	4416.079	0.660	69	3335.820		0.927	22
		C	4409.270	0.663	83	3418.468		0.919	24

GWR Coefficients

The linear relationship of *core* with *area*, *perimeter* and *mean_slope* was not constant across each study site (Table 14). Variability in the GWR Model slope coefficients suggested non-stationarity of all the datasets. Without a Monte Carlo test for spatial stationarity, the significance was not known (Brunsdon et al. 1996, Fotheringham et al. 2002, Kupfer and Farris 2007, Zhang et al. 2008). *Perimeter* coefficient margin of difference increased at site 1 and 2 but decreased at site 3. All three variables displayed non-stationarity by the variation in coefficient range of values.

Global and Local Moran's I for GWR Residuals

As indicated by Figure 16-1 - 3 and Table 14, the Global Moran's I correlogram and the Local Moran's I map did not appear to relate to each other in a consistent manner. For example, the correlogram had no autocorrelated values at site 1 and at site 3 had one value in 1977 at 1200 m. However, the local statistic map indicated hot and cold spots at both sites and showed that the number of autocorrelated residuals (600 m distance) at site 3 increased from 13 to 24 between 1977 and 2007 (Table 13). At site 2 the Local Moran's I map at 600 m distance class indicated positive and negative autocorrelated clusters in the northeast section of the site in 1963 that drifted south from 1980 to 2007. The global statistic did pick up the negative cluster in 1963 at 600 m. However, from 1985 to 2007 there were no autocorrelated values at 600 m. Scatter plots of GWR estimated and standard residuals indicated the presence of outliers in each dataset. Site 1 outliers constituted large *forest* LULC class polygons until 1997 when the new Highway 27 *transportation* polygon was added. *Transportation* LULC class represented all outliers for years at site 2 and 3.

Table 14 Comparison of parameter estimates of OLS and GWR model C. Without a Monte Carlo test for spatial stationarity, the significance of the variability in the GWR model slope coefficients was unknown. However, the trend over the years in general was an increase in non-stationarity (heterogeneity) of the relationship of *core* with the *area* indicator variable for all 3 sites.

	Yr	**OLS β1 *area***	**Range GWR *β*1 *area***			**OLS β2 *Perim***	**Range GWR β2 *Perim***			**OLS β3 *Mean Slope***	**Range GWR β3 *Mean slope***		
1	1963	0.3844	-0.6902	-	1.0853	0.0001	-0.004	-	0.004	-0.5035	-1.310	-	6.688
1	1972	0.3691	-0.3548	-	1.0250	0.0001	-0.004	-	0.003	-0.2585	-0.804	-	4.058
1	1980	0.2488	-0.4328	-	1.0254	0.0002	-0.003	-	0.004	0.1033	-0.852	-	6.502
1	1997	0.3141	-1.6731	-	1.2915	0.0003	-0.003	-	0.011	-0.5794	-3.476	-	5.717
1	2007	0.3453	-1.7470	-	1.2388	0.0003	-0.002	-	0.011	-0.7797	-3.233	-	3.170
2	1963	0.3368	-0.7472	-	1.3975	0.0002	-0.003	-	0.006	-1.2162	-4.112	-	3.344
2	1985	0.0719	-1.5042	-	1.0548	0.0005	-0.001	-	0.008	0.2873	-5.389	-	1.613
2	1997	0.0963	-1.5928	-	1.0618	0.0005	-0.002	-	0.009	0.0008	-12.977	-	2.122
2	2007	0.1151	-1.5460	-	1.0648	0.0005	-0.002	-	0.008	-0.0915	-12.577	-	1.899
3	1977	0.3475	-1.4017	-	0.8951	0.0002	-0.004	-	0.007	-0.8020	-3.950	-	4.537
3	1984	0.4001	-1.2281	-	0.8829	0.0002	-0.005	-	0.007	-0.8450	-5.831	-	4.477
3	1997	0.4123	-1.3115	-	1.2119	0.0002	-0.006	-	0.008	-0.7962	-8.633	-	10.993
3	2007	0.4415	-1.1795	-	1.4864	0.0002	-0.003	-	0.006	-0.8321	-4.208	-	4.828

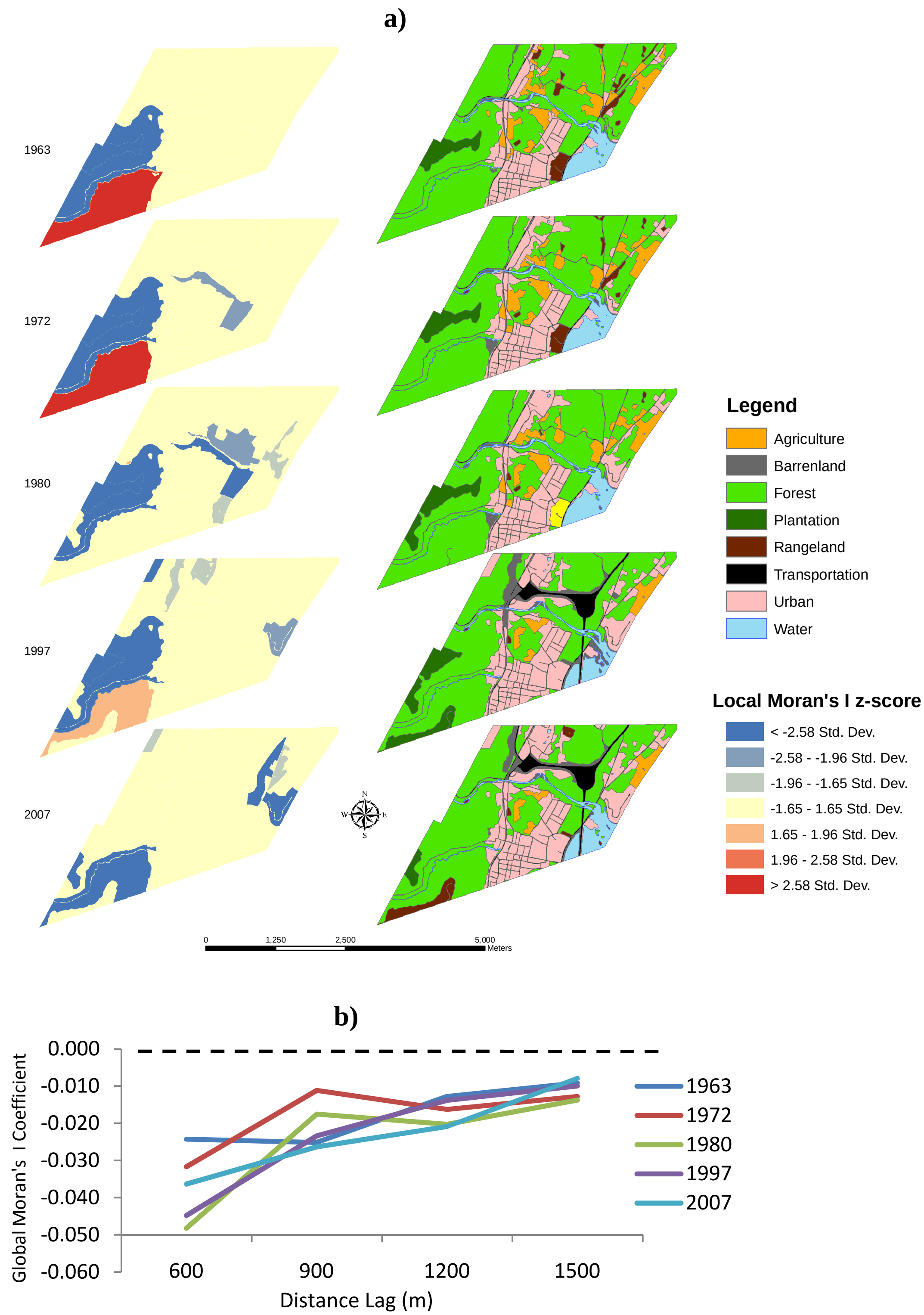


Figure 16-1. Site 1 GWR Model C autocorrelated residuals. **(a)** Local Moran's I plot of residuals indicated autocorrelated values at 600 m that disperse over the years. **(b)** Global Moran's I correlogram of residuals did not indicate autocorrelated structures at distance 600 m thru 1500 m. The Global Moran's I Coefficient was standardized; positive autocorrelation values ranged from 0 ≥ to 1, negative values range from 0 to ≥ -1.

a)

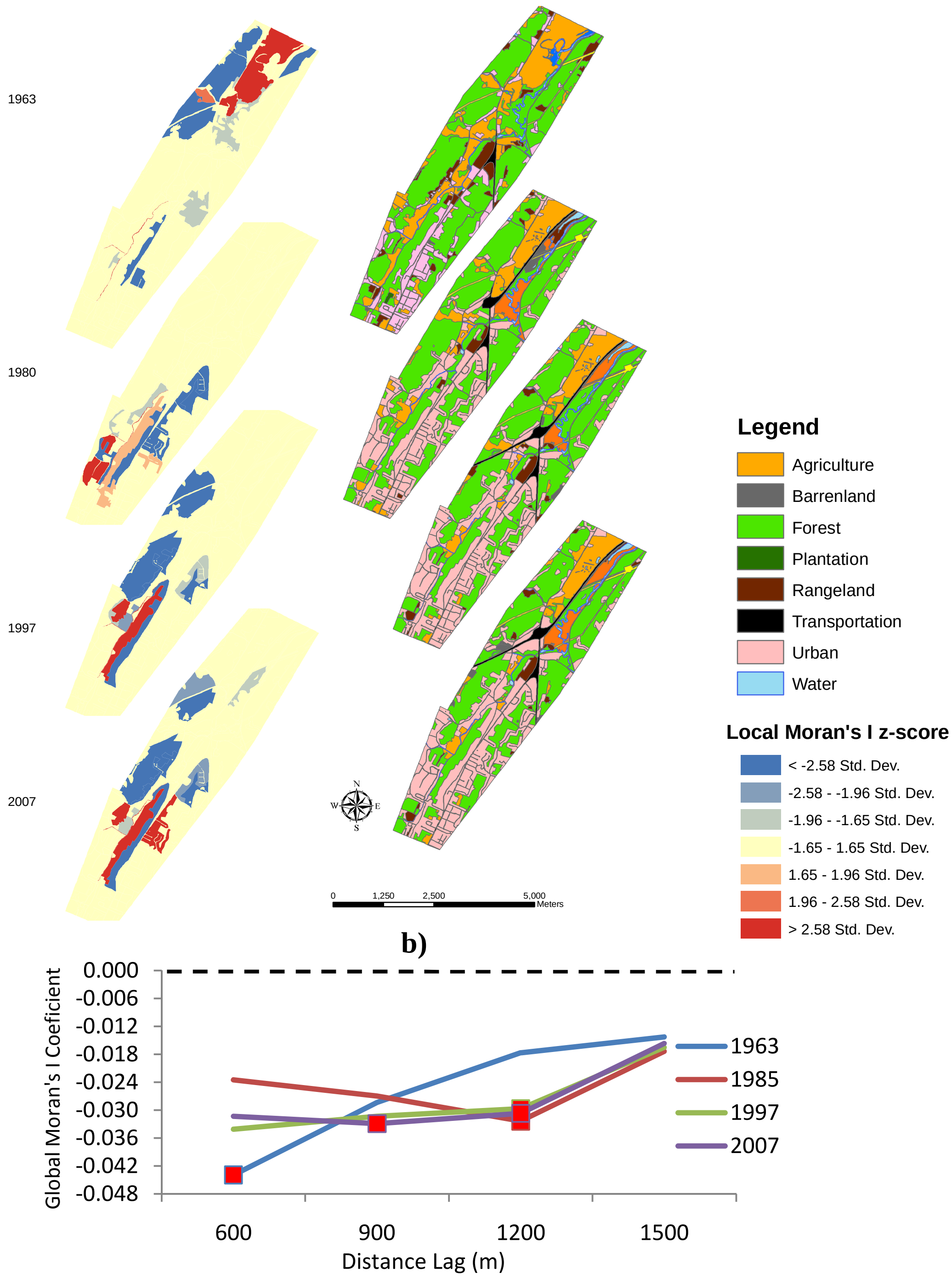


Figure 15-2. Study Site 2 GWR Model C autocorrelated residuals. **(a)** Local Moran's I plot of residuals at 600 m distance class agreed with global statistic in 1963. Autocorrelated structures shifted direction, from northeast of study area in 1963 and over the years drifted south. **(b)** Global Moran's I correlogram of residuals. Red symbols indicated significant values at $p \leq 0.05$. At 1500 m the trend was becoming random as it approached 0. In the absence of autocorrelation an expected value was slightly negative and close to 0. As the strength of a process decreased with distance, values of spatial autocorrelation decreased and the trend observed could be used to characterize spatial pattern (Fortin and Dale 2005).

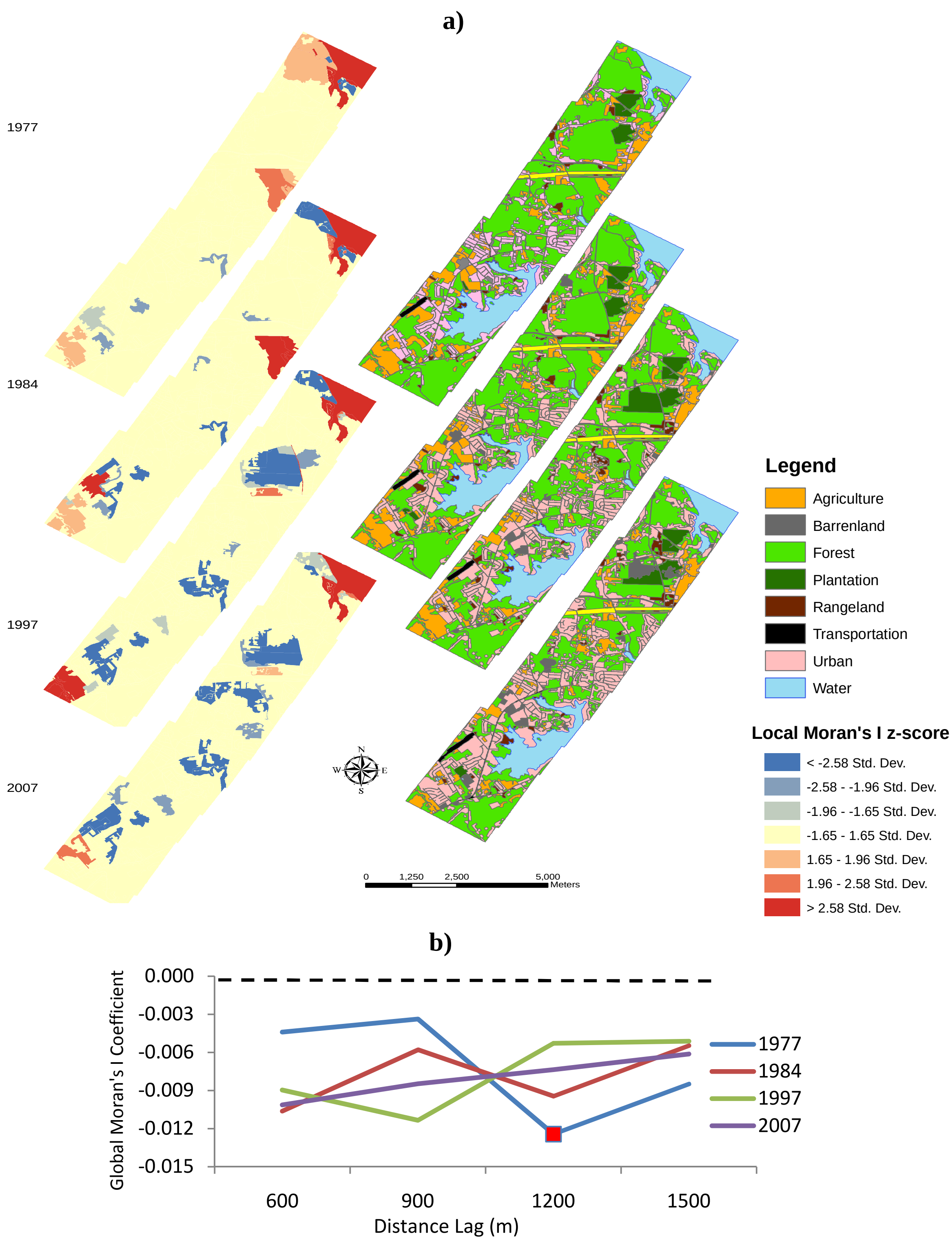


Figure 15-3. Study Site 3 Model C GWR autocorrelated residuals. **(a)** Local Moran's I map of residuals at 600 m distance did not relate to global statistic. Negatively autocorrelated structures increasingly dispersed over the site from 1963 to 2007. **(b)** Global Moran's I correlogram of residuals.

DISCUSSION

Exurban Development

Change in land use class and patch area over time was used as a proxy for the six phases of landscape fragmentation conceptualized by Forman (1986) and modified by Jaeger (2000), which were perforation, incision, dissection, dissipation, shrinkage and attrition. Landscape change studies with heterogeneity indices have been reported to function as surrogate measures to conceptualize how ecological processes changed over time (Gustafson 1998).

Total land cover class area has been reported to be a reliable index in scaling relations (Wu 2004) and has been widely used in habitat studies (Fauth et al. 2000, Gustafson et al. 1994, Tidd et al. 200l) and in habitat fragmentation studies with a shape index (Bender et al. 2003). Class level statistics have indicated that over the last 40 years the area of potential habitat has decreased. Surprisingly, all three sites had a lower *total edge* for potential box turtle habitat over time. This was a result of disturbance patches (i.e., urban and transportation) coalescing in size over time, which caused the edge density to decline in habitat patches that were contiguous to the disturbance patches (Hargis et al. 1998). Donovan et al. (2002) reported similar results with *total edge* in a temporal study of songbird habitat in a fragmented, forested landscape.

The response of freshwater turtle populations in South Carolina to the *edge effects* of habitat fragmentation was measured by Burke and Gibbons (1995) who recommend a 275 m upland buffer zone to protect all nest and hibernacula sites. Vos and Chardon (1998) found that roads within 250 m of a Moor Frog (*Rana arvalis*) reproduction site affect the population size negatively. Forman (2000) estimated in general, a minimum 305 m (each side) road buffer as the ecological road-effect zone for primary roads in woodland and for secondary roads 200 m (each side).

Number of forest patches, largest forest patch and *mean patch size* have commonly been used to measure habitat reduction and fragmentation (Gardner and Urban 2007). I used *area weighted mean patch size* instead of *mean patch size* to characterize forest trends because the distribution of patch sizes was asymmetric; hence the mean was not a suitable descriptor (Freeman et al. 2003, Gardner and Urban 2007, Pearson et al. 1999, Turner et al. 2003).

Average, roadless area (ha) of a patch of landscape in site 3 has decreased in size, twice as much over time as in study site 1 and three times as much as the average landscape patch in study site 2. Structural change in the pattern of urban buildup along the highways over time could be observed when one looked at the land cover change maps. "Structural changes in landscapes such as highway construction and development or shifts in markets and urban centers, may introduce new drivers to the system or change the influence of others" (Bürgi and Turner 2002, 198). The Highway 111 construction in 1980 on study site 1 and Highway 27 in 1960 on site 2 accelerated fragmentation across each landscape.

The proximity of site 3 on the Tennessee River floodplain which encompassed the Dallas Bay portion of Chickamauga Lake may influence the rate of change on this site. A temporal land use study of two lakes in Wisconsin using 1937 historic photography was conducted by the US Long Term Ecological Research Network (LTER) and the results suggested that "lakes are playing a bigger role in the evolution of the terrestrial landscapes surrounding them" (Riera et al. 2001). Over 75% of site 3 was unincorporated and under a great deal of development pressure. Hamilton County recorded 241 new subdivisions, between 2001 and 2005; and, half of these were in unincorporated areas (Development Trends Hamilton County, TN 2001 - 2006).

Weng (2007) found that urbanization was positively related to fragmentation. The urban and forest patches in site 2 have changed significantly in area and perimeter since 1963 and the rate of *core* habitat loss at site 2 was the highest of all 3 sites at 5.52% per year between 1997 and 2007. There was a 59% loss of farmland in Site 2 since 1963, compared to an 8% loss for site 1 since 1963 and a 40% loss for site 3 since 1977. These results reflected the findings of Brown et al. (2005) that in the southeastern United States, forest and agricultural cover have decreased while urban and mechanical disturbances increased in area between 1973 and 2000. The Chattanooga Times Free Press reported in their August 12, 2008 issue that the dramatic increase in the average value per acre of farmland in Tennessee was being driven by developers buying farms to build subdivisions. The USDA National Agricultural Statistics Service reported that the values of farms in Hamilton County have doubled from 1987 to 2002. Regional studies have forecasted a continuing increase of development pressure in the Ridge and Valley ecosystem through 2020 (Wear and Greis 2002, NASA Land Cover Land Use Change Program, http://landcovertrends.usgs.gov/east/eco67Report.html).

Species habitat requirements and ecological processes have been implicated by how humans shape the pattern of the landscape (Cifaldi et al. 2004, Pearson et al. 1999, Turner 1989). Human induced change such as land ownership effects (Turner et al. 1996) has been a nonlinear phenomenon (Fahrig 1998), which influences linear methods of measurement and characterization of landscape heterogeneity (e.g., the complexity and variability of a landscape mosaic) and habitat fragmentation.

Biodiversity Loss and Fragmentation

The vulnerability of box turtle populations to extinction risk because of loss of habitat can be determined by measuring how quickly their habitat has achieved its current state and scale future rate of habitat loss with the demographic potential of turtle populations (Schrott et al. 2005a). Populations subjected to a slow rate of habitat loss (i.e., < 0.5% per year) could remain relatively stable because the re-generation rate could compensate (Schrott et al. 2005a).

Site 1 gained 2% *core forest* habitat per year between 1997 and 2007, which suggested that it was possible for a population to persist. The rate of change has been erratically fluctuating over the last 40 years. Between 1963 and 1971 the rate of change per year was a slow 0.7% rate of loss, then the rate increased to 4% per year between 1972 and 1980, but slowed down between 1980 and 1997 to 0.4% a year and between 1997 and 2007 has been gaining habitat at 2 % a year. Socioeconomic and political variables can create patterns in the landscape not provided in biophysical models such as in this study, "understanding and predicting land cover requires knowledge about land ownership" (Turner et al. 1996, 1169; Appendix G). For example, one of the largest turtle habitat patches on site 1 was bulldozed by mountain stone strip mining activities that have been ongoing since late 2006 in a section of Cumberland Trail State Park. The state owned the land in the park but the mineral rights were held by a private company. Specifically, the Chattanooga Times Free Press reported in their February 15, 2008 issue that a section of the trail near Posey Point had to be closed due to damage from strip mining (Appendix H).

Site 2 followed a similar pattern as site 1, but unlike site 1, it lost over 3% of *core forest* habitat per year between 1997 and 2007. Rate of *core forest* loss on site 2 was at the same rate as a population can produce one generation of turtles. Potentially, a population of turtles at this site would be functionally extinct because it was unlikely the population would compensate for this rate of loss; and, in 6 years all *core forest* habitat would disappear. Between 1997 and 2007 site 2 was losing 5.52% *core* habitat, twice as fast as *core forest* habitat loss at 3.2% per year.

Site 3 differed from the other two sites because it had a gradient pattern of *core fores*t habitat loss. Between 1977 and 1984 the rate of loss was a slow, sustainable 0.2% a year, then loss increased to 3% a year between 1984 and 1997. Between 1997 and 2007 *core forest* habitat rapidly disappeared at 7.5% per year which suggested a threshold was reached in 1997 when fragmentation rate exceeded the box turtle re-generation rate. Box turtle cohort re-generation time was 2.7% per year. These results suggested that the turtle *core forest* habitat in site 3 disappeared over twice as fast as a population could produce one generation of turtles and in about eight years 50% of *core forest* habitat will be gone. Site 3 lost twice as much *core forest* habitat as *core* habitat between 1997 and 2007.

Based on habitat stability, these results suggested that site 1 was gaining *core forest* box turtle habitat so current turtle populations could continue to persist. Furthermore, site 2 at best may have sustained almost one generation of box turtles until all core habitat was gone but site 3 would not sustain any future generations of box turtles. Site 1 had more topographic relief than sites 2 and 3; therefore, it may not have experienced exurban sprawl to the same degree as sites 2 and 3.

These parameters modeled critical habitat elements at the scale gradient that the box turtle responded to the heterogeneity of the landscape (Weins 1989). Relative to this concept of habitat scale was the realization that “habitat patch” was a useful spatial construct not fixed in space (Turner et al. 2001) but was an artifact dependent on the scale of a box turtle’s perspective (Thompson and McGarigal 2002).

Rates of habitat Loss

Road Density/Small Vertebrates

Fragstats descriptive statistics did not capture the non-stationarity character of the fragmentation process. Exploratory spatial analysis could model the stationarity changes specific to each site because the hills and valleys representative of this geographic region created complex relationships between parameters that varied over space (Brunsdon et al.1996). Regression coefficients of the GWR Model displayed a range of variability, which suggested non-stationarity, compared to the constant OLS coefficient value. The OLS Model under estimated coefficients compared to the GWR model which indicated the global statistic was sensitive to outliers. However, analysis of GWR Model coefficient parameters provided little insight into patterns or rate of land use change. The reason for this may have been because the *core* dependent variable was not normally distributed, or because outliers were present in the datasets.

Spatial distribution of *mean_slope* values at sites 1 and 3 did not vary over the years. It was not surprising that *mean_slope* values at sites 1 and 3 did not vary over the years because it was not expected that degrees slope will vary over time as much as *area* or *perimeter*. The *mean slope* independent variable of the OLS model C had a significant negative relationship with *core* at site 3 for all years and in 1972 at site 2, but was not significant at site 1 or at site 2 in 1985 and 1997. This seemed counter intuitive since site 3 had the least variation in slope compared to site 1 and 2, hence had the lowest SD (±0.62 in 1977) for mean slope of all 3 sites (in 1963 site 1 had ±0.88 SD and site 2 had ±0.72 SD). The global measure more than likely was influenced by outliers which would suggest caution in interpreting those results.

Significantly autocorrelated residuals suggested fragmentation behavior. Site 3 number of autocorrelated residuals almost doubled between 1977 and 2007. These results were in agreement with the reported accelerated rate of core habitat change at site 3. The pattern of significant residuals between each decade may have given some clue of the mechanics of habitat loss and land use change. For example, features that were increasing isolated and negatively correlated. Underlying processes could have created a pattern of autocorrelated residuals and may have been related to four factors:

1. A missing environmental predictor in the model
2. Unaccounted for biotic processes
3. Incorrect model specification
4. Effects from changes in scale (i.e., resolution and spatial extent; Fortin and Melles 2009).

It has been reported that spatial patterns of continuous variables could be analyzed using indices of spatial autocorrelation such as Local Moran's I that measured the similarity or dissimilarity of any pair of neighbors (Shi and Zhang 2003, quoted by Zhang et al. 2008). Spatial autocorrelation of model errors (residuals) could reflect the spatial pattern of variables modeled. In this study, *core* habitat exhibited increasing negative autocorrelation as heterogeneity of patches (fragmentation) increased over the years.

The Local Moran's I statistic was used to decompose the Moran's I global values. If the Global Moran's I results were autocorrelated, the local statistic could have identified the clusters or, if the global results were non-stationary, the local statistic could have identified outliers (Anselin 1995). The pattern demonstrated by the Local Moran's I was not consistent with the pattern indicated by the Global Statistic, which suggested that the processes modeled by the local indicators were not stable because parameter coefficients values had a range of variation across the site. These local values were very different from the mean value, and contributed more to the global statistic (Anselin 1995).

The Global Moran's Coefficient was an average value of spatial autocorrelation for all spatial locations (Fortin and Melles 2009). This statistic was sensitive to outliers; and, the GWR regression scatter plots of estimated and residual showed outliers in each dataset. The Global Moran's Coefficient was omnidirectional, and it estimated the distance between locations but did not measure the direction, so the spatial pattern as determined by the Global Moran's I did not take into account anisotropy (Fortin and Dale 2005). However, the Local Moran's I Statistic could have demonstrated directional local pattern that may have been an indication of non-stationarity, which suggested a fragmentation process in the data.

DIRECTIONS FOR THE FUTURE

Reptiles and amphibians are the most under-represented in habitat fragmentation studies (McGarigal and Cushman 2002).   Habitat fragmentation articles were surveyed by McGarigal and Cushman (2002) and they found only 4% out of 134 articles are of reptiles. This study defines suitable Eastern Box Turtle habitat within three study sites and suggests that the stability of current populations may be imperiled and the future of populations will be at risk with the current rate of habitat fragmentation and loss. Empirical field studies are needed to map the distribution of occupied and empty habitat (Thomas and Hanski 1997) and to determine how sensitive populations are to the rate of habitat loss and fragmentation. Similar studies such as this can be used to communicate to Hamilton County elected officials, the Regional Planning Agency and the development community to incorporate rationale behind planning decisions that incorporate eastern box turtle conservation along with economic development. More work needs to be done to quantify the historic variability of landscape pattern in the context of ecological processes (Gustafson 1998, Turner et al. 2001) and to create habitat maps from an organism-based rather than a strictly human perspective (Wiens 1976).

Road Effects

Exchange of box turtles in the landscape matrix between habitat patches “will decrease due to the extra mortality on roads, which will lower colonization rates, and increase the extinction risk of local populations” (Vos and Chardon 1998, 50). Because box turtles are habitat generalists that have low reproductive rates and long generation times they are more susceptible to road mortality than other habitat effects associated with roads (Forman et al. 2003, Forman and Deblinger 2000). For example, turtles move slow but can be mobile in the landscape matrix and as such are more vulnerable to road mortality. Road mortality is linked to box turtle habitat loss because studies suggest that when mortality rate in the matrix is high (such as when roads are present), mobile species are actually more vulnerable to habitat loss (Aresco 2003, Gibbons et al. 2000, Forman et al. 2003).

Permeability of the Matrix

Proximity of remaining habitat patches and neighboring habitat distance change in landscape depends greatly on three characteristics of the landscape matrix (Forman and Godron 1986):

1) The area of the matrix relative to other land cover types
2) The level of connectivity between land cover types within the matrix
3) The degree of control the matrix has over landscape dynamics

Site 1 matrix permeability is particularly constrained by the topography (i.e., steep slopes of escarpment). The permeability of the matrix by dispersing turtles is “a function of distance to neighboring habitat and matrix quality” (Hilty et al. 2006, 126). Box turtles use two distinct habitats, forest and meadow are used by adult turtles and juveniles exclusively, and upland open land is used by females for nesting and males at times. The measure of proximity of critical habitat types and how well box turtles can move between them is critical (Dunning et al. 1992, Pope et al. 2000).

Steep Slopes

Half of Hamilton County’s natural resources that are forested are on terrain greater than a 15% slope (Comprehensive Plan 2030) (100% slope is 45° so 15% slope is 6.6°). Forested and extremely steep terrain (>15% slope) may not be suitable habitat for the eastern box turtle. In the southeastern US. Muegel and Claussen (1994) find that box turtles are adept going up grades to 40° but they are more limited in descending slopes -10° to -40°.

Habitat Conservation

Gradual rate of habitat loss (<0.5%/yr) increases the success of habitat restoration efforts (Schrott et al. 2005b). This study suggests that Study sites 2 and 3 have accelerated rates of habitat loss (Table 12A and Table 12B), so the rate of loss in those sites would have to be slowed down for suitable restoration sites. Success also depends on the box turtle demographic potential of each habitat patch (Gustafson et al. 2005).

Considerations

Conservation plans for box turtles are constrained by four factors. First, dispersal mortality is high for box turtles in the road matrix (Dodd 2001, Klemens 2000) which will constrain the potential for habitat fragments to “mitigate effects of habitat loss” (Fahrig 2001, 72). Fahrig suggests that conservation strategies consider matrix quality and include structures such as fence rows to provide a “microclimate and shelter from predators” (Fahrig 200l, 72). Box turtles are also especially vulnerable to fragmentation because individuals have limited ability to successfully migrate between isolated patches, so potential of individuals to “rescue” dwindling populations from extinction is limited (Klemens 2000, Thomas and Hanski 1997, 213). It may be more important to provide box turtles with enhanced quality habitat than maintain connectivity in a fragmented landscape by providing cleared, upland nesting sites for females and supplementing food resources (With and King 1998). The second factor is the eastern box turtle level of sensitivity to habitat loss. Dodd (2001) believes that the loss and alternation of box turtle habitat is the single greatest threat to their continued existence. Hence a third factor is the vulnerability of box turtles and their nesting sites to habitat / matrix edge effects. For example, urban edges increase predation by raccoons and dogs and the collection of adult turtles by humans (Klemens 2000). Agriculture and forest interfaces are threatening to box turtle populations because of human induced mortality from crop mowing. Nazdrowicz et al. (2009) recommends that agricultural fields adjacent to a forest be planted with crops that are not mowed or if they are, mowed at a height of > 15 cm. The fourth factor is the homing behavior of the eastern box turtle. Relocation is not a suitable option for conservation of the box turtle because displaced turtles will attempt to return to their original home range as a result of a homing mechanism (Hester et al. 2007). This displacement could expose the turtle to a life-threatening, inhospitable matrix (Hester et al. 2007).

Klemens suggests that "long term conservation will require protection of metapopulations and ecosystems and [the] creation of open-space reservations that correspond to ecosystem function and realities" (Klemens 2000, 240). If there is any hope for Eastern Box Turtles in Hamilton County, high quality and intense habitat maintenance should be the top preservation priority. A mosaic of habitat is required to support the full range of dynamic ecosystem processes for turtles; these include mesic forest for estivation in summer and hibernaculum in winter and upland edges for female nesting sites. Juvenile box turtles may use forest with dense canopy and understory and high moisture content and dense leaf litter more than adults so these forested areas are particularly sensitive to juvenile recruitment (Jennings 2007). Habitat conservation plans in a fragmented landscape should include forested habitat patches adjoining cleared areas for protection, so box turtles do not move into less desirable, urban areas (Iglay et al. 2007).

Box turtles were listed as near threatened on the 2000 IUCN Red List (Jennings 2007), and it is important that conservation strategies are implemented. It is well documented that box turtles can live longer than a century, and may live longer than any other vertebrate (Ernst et al. 1994) because they have a long generation time; an adult turtle could take approximately 20 years to become viable. For these reasons they show a response lag to habitat fragmentation and loss which delays the detection of population decline (Fahrig 2001). This is further problematic because even though they appear to persist in an urbanizing environment they can become functionally extinct (Ernst et al. 1994, Rockwood 2006, Wilson pers. comm.).

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APPENDIX

Appendix A-1

Landscape and habitat pattern studies using satellite, aerial photography or simulated landscapes.

Satellite		Aerial Photography	Simulated
O'Neill et al. 1996	AVHRR		
		Cifaldi et al. 2004	
		Madden 2004	
Griffith et al. 2000, Saunders et al. 2002	Landsat TM		
Gustafson and Parker 1994	Landsat TM		
			Hargis et al. 1998
		Donovan and Flather 2002	
		Thompson and McGarigal 2002	
			Bender et al. 2003
Gustafson and Gardner 1996	Landsat TM		
Riitters et al. 1997	Landsat TM		
Fauth et al. 2000	Landsat TM		
Tischendorf 2001	Landsat TM		
Gardner et al. 2007	Landsat TM		

Appendix A-2

Land cover and habitat change studies, including studies using a combination of satellite and aerial photography or simulated landscapes.

	Satellite	Aerial Photography	Simulated
Wickham et al. 2007	Landsat TM (30 m) resolution for 1984 – 2001		
Bürgii et al. 2002	1992 Landsat TM with 1938 tabular survey data		
Pearson et al. 1999	Landsat MS		Land-use Change System model (LUCAS) projected
Tidd et al. 2000	1963 espionage satellite imagery (resolution 200 m) and Landsat MS (resolution 79 m) for the years 1973, 1984 and 1993		
Turner et al. 1996	1975, 1980, 1986 and 1991 Landsat MS and 1991 Landsat TM		
Wear and Bolstad 1998	1990 Landsat TM imagery	1950 panchromatic aerial photography at 1:20,000 scale	
Turner et al. 2003	1990 Landsat TM imagery, 1970 Landsat MSS and projected to 2030	1950 panchromatic aerial photography at 1:20,000 scale	
Freeman et al. 2003		1937, 1938, 1940, 1965, 1967 and 1968 (1:20,000 scale) 1990	
Hawbaker et al. 2006		1937 and 1999	
Bartell et al. 2002		1967, 1987, 1943 1994	

Appendix B

Summary of Natural history of Terrapene carolina carolina

Terrapene carolina carolina is found in Eastern North America in open woodlands, pastures and marshy meadows (Ernst et al. 1994) and has been one of the most common terrestrial reptiles in the eastern United States (Claussen et al. 1991). The natural plant communities in Northern Hamilton County are mostly Dry-Mesic Oak Forest of Middle and East Tennessee and Xeric-Dry Oak Forest of Middle and East Tennessee (Tennessee GAP Analysis Land Cover Manual 2006). According to species habitat association information obtained from the Tennessee Wildlife Resource Agency (TWRA), *Terrapene carolina carolina* inhabits all of the plant communities in Tennessee (GAP database file obtained from TWRA 2007). Eastern Box Turtles like to over winter on moist, south, southwest slopes (Dodd 2001) in at least a .8 cm deep hibernaculum within the soil and a thick mat of leaf litter cover at least 10 cm deep (Dolbeer 1971), or they may spend the winter in the muddy bottom of a puddle (Ernst et al. 1994).

Donaldson and Echternacht (2005) observed box turtles in Tennessee thermoregulating by spending weeks at a time during the summer submerged in pond mud. *Terrapene carolina* living in isolated and fragmented habitat patches in Delaware have been observed to move around less frequently than turtles in more favorable habitat (Iglay 2007) but home range areas may be larger in unfavorable habitat (Stickel 1948, 1950). Experiments with captured box turtles from Ohio in the laboratory report that box turtles are good at going up grades up to 40˚ but have limited ability to descend slopes (-10˚ to -40˚) (Muegel and Claussen 1994). It is known that female turtles can travel long distances to find suitable nesting sites and male turtles can make frequent and long movements in search of mating opportunities (Gibbons 1986). Nesting generally occurs in June, the female prefers just before, during or after rainfall in the afternoon (Dodd 2001). Flitz and Mullins (2006) studied 24 female box turtles in Illinois all of which nested in open, disturbed clearings. The subjects of the study had some daily straight line movements greater than 500 meters prior to nesting. It is generally agreed that box turtles prefer an open, elevated patch of sandy, loamy soil for nesting (Ernst et al. 1994). Home range of a box turtle is the area normally traveled in its activities and territory is a defended area that may include home range or part of a home range (Stickel 1950).

Juvenile and adult box turtles may exhibit differential habitat use. On Egmont Key in Florida Jennings (2007) found that juveniles rarely used open areas but used areas with leaf litter, and soil more frequently, substrates with high moisture content (>75%) dense cover at low, mid-story, and canopy heights. Precipitation stimulates increased movement and facilitates foraging in terrestrial species like *Terrapene carolina* (Shepard et al. 2008a).

Appendix C

Fragstats Metric Description

Patch Level Metrics

Area - Calculates area in hectares

Proximity Index (PI); (unitless) – First, the **search radius** is specified (i.e., the distance [in meters] from a focal patch within which neighboring patches are evaluated). PROX equals the sum of patch area (m^2) divided by the nearest edge-to-edge distance squared (m^2) between the patch and the focal patch of all patches of the corresponding patch type whose edges are within a specified distance (m) of the focal patch, as opposed to the nearest-neighbor distance of each patch within the search radius, which could be to a patch other than the focal patch. This study uses a 300 m search radius buffer distance (Distanced determined for core habitat in other habitat models and the average box turtle home range diameter). This metric sums the ratios of patch area to distance for all habitat patches that fall at least partially within some specified distance of the focal patch and is based on patch edge-to-edge distance, computed from cell center to cell center. Index is based on Island Biogeography theory and is a measure of isolation.

Range – PROX > 0. PROX = 0 if a patch has no neighbors of the same patch type within 300m search radius. PROX increases as the neighborhood (defined by the specified search radius) is increasingly occupied by patches of the same type and as those patches become closer and more contiguous (or less fragmented) in distribution. The upper limit of PROX is affected by the search radius and the minimum distance between patches.

Euclidian Nearest Neighbor (ENN); (unit m) - Distance between patches of the same class based on edge-to-edge distance.

Shape Index (SI); (unitless) - Equals patch perimeter (m) divided by the square root of patch area (m^2). SI equals 1 when all patches are circular (or square in raster) and increases without limit as the patch shapes become more irregular.

CORE (ha) - Equals the area (unit m^2) within the patch that is further than the specified depth-of-edge distance from the patch perimeter divided by 10,000 (to convert to ha). CORE equals 0 when every location within the patch is within the specified depth-of-edge distance from the patch perimeter. CORE approaches AREA as the specified depth-of-edge distance(s) decreases and as patch shape is simplified (McGarigal et al. 2002).

Class Level Metrics

Class Area (CA); (units ha) **-** ∑ areas (m^2) of all patches of the corresponding patch type divided by 10,000 to convert to hectares Area of patch class.

Number of Patches (NP) - Number of patches in respective land cover class.

Percent land (CPLAND); (unit %) - Area (m^2) of corresponding patch type divided by total landscape area, multiplied by 100 (to convert to a percentage) Percent of land cover class.

Patch Density (PD); (unit - number per 100 ha) - Equals the number of patches of the corresponding patch type divided by total LS area, multiplied by 10,000 and 100 (to convert to 100 hectares). (n/total LS area)*10,000.

Total Edge (TE); (unit m) - ∑ lengths (m) of all edge segments involving the corresponding patch type. Equals 0 when there is no class edge in the LS; that is, when the entire landscape consists of the corresponding patch type. Includes a user-specified proportion of background edge segments involving corresponding patch type.

Mean Shape Index (SHAPE_MN); (unitless) - Average patch shape complexity for patches comprising the class; equals 1 when all patches are circular and increases as patches become noncircular.

Area Weighted Mean Shape Index (SHAPE_AM); (unitless) - When sampling relatively small areas, the AWMSI is considered more meaningful than MSI because it gives greater weight to large polygons (see Perry et al. 2002).

Area Weighted Mean Core Area (CORE_AM); (%) **–** Sum of the core areas of each patch (m^2) of the corresponding patch type, divided by the sum of the areas of each patch (m^2) of the same type multiplied by 100 (to convert to percentage).

Area Weighted Mean Patch Size (AREA_AM); (ha) **–** Computed by dividing the summation of the squared patch sizes (see Turner et al. 1996, Gardner et al. 2007).

Mean Patch Size (AREA _MN); (ha) - Average size of the patches comprising the class.

Median Patch Size (AREA _MD); (unit ha) - Median size of patches comprising the class.

Patch Size Range (AREA _RA); (unit ha) - Range size of the patches comprising the class.

Standard Deviation Patch Size (AREA_SD)

Patch Size Coefficient of Variation (AREA_CV); (%) - Measures relative variability about the mean. Only use with MPS (see Cifaldi et al. 2004).

Largest Patch Index (LPI), (%) - Equals the area of the largest patch of the corresponding patch type divided by total landscape area, multiplied by 100 (to convert to a percentage). In other words, equals the percent of the landscape comprised by the largest patch.

Mean Core Area (CORE_MN); (units ha) - The area remaining after removing the area of edge influence, which is defined by buffering the patch with a specified edge effect distance inward from the patch boundary. The sum of the core areas of each patch (m^2) of the corresponding patch type, divided by the number of patches of the same type, divided by 10,000 (to convert to hectares).

Core Area Index Mean (CAI_MN); (unit %), weighted mean (aka TCAI) -Quantifies core area for the entire class as a percentage of total class area.

Landscape Level Metric

MESH (units ha) - Area Weighted Mean Area (ha) Equals 1 divided by the total landscape area (m^2) multiplied by the sum of patch area (m^2) squared, summed across all patches in the landscape. MESH is maximum when landscape consists of a single patch. A lower limit is achieved when the landscape is maximally subdivided; that is, when every cell is a separate patch. MESH and area-weight mean patch size are almost identical. AREA_AM gives the area-weight mean patch size, where the proportional area of each patch is based on total landscape area.

Appendix D

Dry-Mesic Oak Forest of Middle and East Tennessee (based on aspect): These forests are found in the Interior Low Plateau, Cumberland Plateau, Ridge and Valley, and Unaka Mountains Physiographic Provinces. Dominant trees include sugar maple (*Acer saccharum)*, chinquapin oak (*Quercus prinoides)*, white oak (*Quercus alba)*, scarlet oak, (*Quercus coccinea)*, northern red oak (*Quercus borealis)*, black oak (*Quercus nigra)*, hickory species (*Carya sp.*), chestnut oak (*Quercus prinus)*, and southern red oak (*Quercus rubra*). Hydrologic conditions range from dry to mesic.

White oak dominated forests are the most widespread in the Ridge and Valley with the greatest frequency being on mesic sites (Martin 1989). Northern red oak is a common associate here (Martin 1989). In the Cumberland Plateau, these forests are found on drier upper slopes of ravines to middle and lower slopes (Hinkle 1989). American chestnut *(Castanea dentata)*, an extinct alliance replaced in part by chestnut oak, northern red oak, and red maple, was found in the provinces east of the Cumberland Plateau, with a low American chestnut component in the Cumberland Plateau (Hinkle 1989). In the Eastern Highland Rim, mesic upland forests are quite abundant, where historically, American chestnut comprised a significant component of forest (McKinney 1989).

Mixed Mesophytic Hardwood Forest: These forests are found in the Mississippi Alluvial Plain, Loess Plain, Southern Coastal Plain, Interior Low Plateau, Cumberland Plateau, and Ridge and Valley Physiographic Provinces. Dominant trees are sugar maple, chinquapin oak, American beech (*Fagus grandifolia*), tulip tree (*Liriodendron tulipifera*), white oak, northern red oak, bitternut hickory (*Carya cordiformis*), sweetgum (*Liquidambar styraciflua*), Appalachian basswood (*Tilia heterophylla*), and yellow buckeye (*Aesculus flava*). Hydrologic conditions range from sub-mesic to mesic. In the Cumberland Plateau, these forests are found in protected sites of escarpment slopes, coves, and deeper ravines (Hinkle 1989). In the Eastern Highland Rim, mixed mesophytic forests are not common but are occasionally found in coves and gorges (McKinney 1989).

Xeric-Dry Oak Forest of Middle and East Tennessee (based on aspect): These forests are found in the Interior Low Plateau, Cumberland Plateau, Ridge and Valley, and Unaka Mountains Physiographic Provinces. Dominant trees are white oak with southern red oak and post oak (*Quercus stellata*); as well as chestnut oak with scarlet oak and black oak. Blackjack oak (*Quercus marilandica*) may be found with these on the driest sites (Clebsch 1989). Common associates include tuliptree, elm (*Ulmus sp.*), maple (*Acer sp.*), and black walnut (*Juglans nigra*). Hydrologic conditions range from xeric and subxeric to dry.

In the Cumberland Plateau and Cumberland Mountains, this mixed oak forest is found on uplands (Hinkle 1989). In the Eastern Highland Rim, subxeric oak-hickory forests are found on many upland slopes and on xeric ridges (McKinney 1989). Also on the Eastern Highland Rim, xeric and sub-xeric upland flatwoods are dominated by southern red oak, post oak, blackjack oak, and scarlet oak (McKinney 1989). American chestnut, an extinct alliance once found in Middle and East Tennessee, was replaced in part by stands of chestnut oak, northern red oak, and red maple.

In the Ridge and Valley, white oak-dominated forests are the most widespread forest community and they occupy a wide range of soils and landforms except the most extreme wettest and driest

(Martin 1989). On the drier sites, chestnut oak, black oak, and other upland oaks become important (Martin 1989).

Xeric to Mesic Mixed Conifer/Hardwood Forest: These forests are found in the Southern Coastal Plain, Interior Low Plateau, Cumberland Plateau, Ridge and Valley, and Unaka Mountains Physiographic Provinces. Dominant trees are eastern red-cedar (*Juniperus virginiana*) with chinquapin oak, post oak, black oak, and blackjack oak; shortleaf pine (*Pinus echinata*) with white oak, southern red oak, post oak, black oak, and blackjack oak; shortleaf pine, loblolly pine (*Pinus taeda*), and/or Virginia pine (*Pinus virginiana*) with white oak, northern red oak and tuliptree. Other combinations are pitch pine (*Pinus rigida*) and/or Table Mountain pine (*Pinus pungens*) with chestnut oak and scarlet oak; Virginia pine with white oak, post oak, southern red oak, and black oak; Virginia pine with scarlet oak and chestnut oak; and shortleaf pine with scarlet oak, southern red oak and chestnut oak. Hydrologic conditions range from xeric, sub-xeric, dry, to mesic.

In the Cumberland Plateau, shortleaf pine-white oak stands represent the typical oak-pine forests (Hinkle 1989). Virginia pine is found on old field sites and is associated with several oak species (Hinkle 1989). In addition several stands of Virginia pine occur on dry promontories above the Tennessee and Cumberland Rivers (Chester and Ellis 1989).

(Referenced from the Tennessee GAP Analysis Land Cover Manual 2006, reprinted with permission from Jeanette Jones, GIS Manager, Tennessee Wildlife Resource Agency TWRA)

Tnveg Metadata

Originator: Tennessee Wildlife Resources Agency
Publication_Date: 1997
Title: Detailed Vegetation of Tennessee
Geospatial_Data_Presentation_Form: raster digital data

Description:
Abstract: The land cover types were derived from classification techniques performed on Landsat TM imagery. The strip mines/rock quarries/gravel pits class were taken from ancillary data sets and added to the classification file. The scrub/shrub class was not attainable for all TM scenes and therefore is not valid for a state-wide representation of that class. It should be noted that the pasture/grassland class includes winter wheat, hay, as well as pasture. The forest classes from the land use/land cover file were extracted from the satellite imagery and reclassified. Forest communities were interpreted from aerial videography acquired April 1995 and correlated to the satellite imagery. The Nature Conservancy, An Alliance Level Classification of the Vegetation of the Southeastern United States (May 1997) was used to guide the labeling process.

Purpose: This map was prepared in compliance with the National Gap Analysis Program effort. The map provides current information on the geographic location and extent of major vegetation and land cover types in the state of Tennessee. The primary purpose of the map is to estimate the current spatial distribution of habitat that is available for terrestrial vertebrate species. The intent of all Gap Analysis

Program products is to provide tools for conservation planning purposes.

Accuracy of the original land use/land cover map for the entire state was 85%.
Subsets taken from the original land cover file were used to map the forest communities.

Appendix E

Study Site 1 potential habitat metrics (Forest). The patch ID number (PID) corresponds to the PID number identifying patches in Core Habitat Maps. A patch is a discrete polygon that is coincident with all other polygons in a dataset.

	PATCH ID	AREA (ha)	PERIM (m)	SHAPE INDEX	CORE (ha)	PROX
1963	103	0.4	324	1.3	0.4	29,851
	64	28.2	6,024	2.8	1.3	6,891
	4	25	6,338	3.2	2.7	12,127
	8	69	6,602	2	2.7	26,086
	65	33.5	5,366	2.3	8.7	23,959
	15	61.1	4,894	1.6	12.3	4,679
	87	99.7	11,148	2.8	21.1	8,354
	151	110	7,952	1.9	85.4	46,475
Total		426.9	48,648		134.6	
1972	7	68.5	6,674	2	0.3	25,655
	51	37.5	4,810	2	8.6	26,089
	14	61.1	4,894	1.6	12.3	4,603
	75	100.3	10,766	2.7	21.1	8,232
	136	105.3	7,104	1.7	84.4	46,477
Total		372.7	34,248		126.7	
1980	87	0.19	232	1.33	0.19	21,349
	5	69.11	6,696	2.01	0.32	25,499
	46	37.79	5,620	2.28	8.5	26,394
	12	61.09	4,894	1.56	12.31	4,574
	69	90.48	11,950	3.14	17.09	8,245
	127	105.07	8,142	1.98	48.42	46,448
Total		363.73	37,534		86.83	
1997	13	50.1	4,870	1.7	0.2	1,336
	5	69.1	6,696	2	0.3	25,499
	73	98.5	10,560	2.7	22	8,232
	133	83.4	8,308	2.3	58.5	46,472
Total		301.1	30,434		81	
2007	18	51.6	5,920	2.1	0.1	1,425
	7	41.4	3,388	1.3	3.1	2,432
	76	117.7	9,898	2.3	36.3	8,235
	133	82.5	8,196	2.3	58.2	46,527
Total		293.2	27,402		97.7	

Study Site 2 potential habitat metrics.

	PATCH ID	TYPE	AREA (ha)	PERIM (m)	SHAPE INDEX	CORE (ha)	PROX
1963	10	Agriculture	11.3	3308.0	2.5	0.1	16768.5
	34	Agriculture	0.3	316.0	1.4	0.3	15862.8
	38	Agriculture	0.5	360.0	1.3	0.5	6226.6
	43	Agriculture	51.5	11438.0	4.0	0.8	12256.9
	40	Agriculture	0.9	902.0	2.4	0.9	12597.3
	37	Agriculture	3.3	1558.0	2.1	3.2	26017.1
	39	Agriculture	4.2	2336.0	2.8	4.1	16907.9
	31	Agriculture	4.5	1090.0	1.3	4.5	3890.8
	82	Agriculture	4.8	1746.0	2.0	4.8	4923.5
	14	Agriculture	13.1	2672.0	1.8	6.1	11435.1
	80	Agriculture	33.8	7046.0	3.0	7.3	17435.5
	46	Agriculture	132.5	14966.0	3.3	73.9	1760.3
	69	Forest	27.6	3902.0	1.9	0.3	21519.9
	81	Forest	27.5	12880.0	6.1	0.3	19221.8
	54	Forest	11.8	1786.0	1.3	0.3	2594.6
	110	Forest	2.6	1568.0	2.4	1.2	10678.5
	116	Forest	51.8	7798.0	2.7	1.4	5061.8
	22	Forest	2.1	1142.0	2.0	2.1	1007.5
	91	Forest	58.6	7596.0	2.5	3.2	1723.3
	134	Forest	4.2	1706.0	2.1	4.2	22945.9
	117	Forest	43.6	6006.0	2.3	4.4	2163.1
	196	Forest	66.2	5798.0	1.8	6.8	8764.7
	157	Forest	40.8	13206.0	5.2	25.2	7486.1
	224	Forest	118.3	11022.0	2.5	75.5	4128.5
	230	TXlineROW	3.1	3842.0	5.5	1.0	4369.2
	298	TXlineROW	5.7	4818.0	5.1	2.7	2372.0
Total			724.6	130808.0		235.1	
1985	141	Agriculture	7.5	2756.0	2.5	0.2	2232.2
	218	Agriculture	3.3	1558.0	2.1	3.2	12487.3
	197	Agriculture	4.2	2336.0	2.8	4.1	4509.3
	122	Agriculture	13.1	2672.0	1.8	6.0	1092.4
	203	Agriculture	16.2	3834.0	2.4	12.0	3723.8
	252	Forest	3.2	1190.0	1.7	0.1	10482.2
	53	Forest	1.0	1434.0	3.5	0.4	1232.6
	96	Forest	1.3	1778.0	3.8	0.9	4067.5
	33	Forest	72.3	5682.0	1.7	1.1	9464.3
	59	Forest	54.4	7112.0	2.4	2.0	1517.2
	98	Forest	44.0	5570.0	2.1	2.7	1650.7
	80	Forest	33.4	7248.0	3.1	5.6	5244.4
	132	Forest	118.5	10360.0	2.4	21.5	2898.7
	29	TXlineROW	9.6	8336.0	6.7	1.0	2379.4
	90	TXlineROW	3.1	3842.0	5.5	1.0	7372.3
	104	Wetland	20.5	3672.0	2.0	4.0	1215.1
Total			405.6	69380.0		65.8	

Continued. Study Site 2 potential habitat metrics.

	PATCH ID	TYPE	AREA (ha)	PERIM (m)	SHAPE INDEX	CORE (ha)	PROX
1997	222	Agriculture	3.3	1558.0	2.1	3.2	10560.9
	202	Agriculture	4.2	2336.0	2.8	4.1	3814.4
	209	Agriculture	13.7	3056.0	2.1	10.0	3722.7
	142	Forest	92.6	10808.0	2.8	0.1	3564.5
	20	Forest	22.7	10572.0	5.5	0.3	9641.5
	134	Forest	9.5	2486.0	2.0	0.3	1469.7
	46	Forest	1.0	1434.0	3.5	0.4	2330.4
	65	Forest	0.9	570.0	1.5	0.9	6592.6
	139	Forest	1.1	744.0	1.7	1.1	7588.9
	52	Forest	54.4	7112.0	2.4	2.0	4295.8
	94	Forest	44.5	5576.0	2.1	2.7	2075.6
	69	Forest	21.1	5260.0	2.9	15.9	2097.0
	77	Forest	36.1	4592.0	1.9	17.4	1528.6
	25	TXlineROW	9.6	8336.0	6.7	1.0	2378.9
	85	TXlineROW	3.1	3842.0	5.5	1.0	7412.7
Total			317.8	68282.0		60.4	
2007	233	Agriculture	3.3	1558.0	2.1	3.2	10560.9
	213	Agriculture	4.2	2336.0	2.8	4.1	3814.4
	221	Agriculture	13.7	3056.0	2.1	10.0	3722.7
	148	Forest	1.1	744.0	1.7	0.2	7514.2
	51	Forest	1.0	1434.0	3.5	0.4	1241.8
	57	Forest	54.4	7112.0	2.4	2.0	1623.6
	80	Forest	36.1	4592.0	1.9	17.4	1428.4
	26	TXlineROW	9.6	8336.0	6.7	1.0	2378.9
	88	TXlineROW	3.1	3842.0	5.5	1.0	7412.7
	107	Wetland	15.9	2806.0	1.8	1.7	1030.8
Total			142.4	35816.0		41.0	

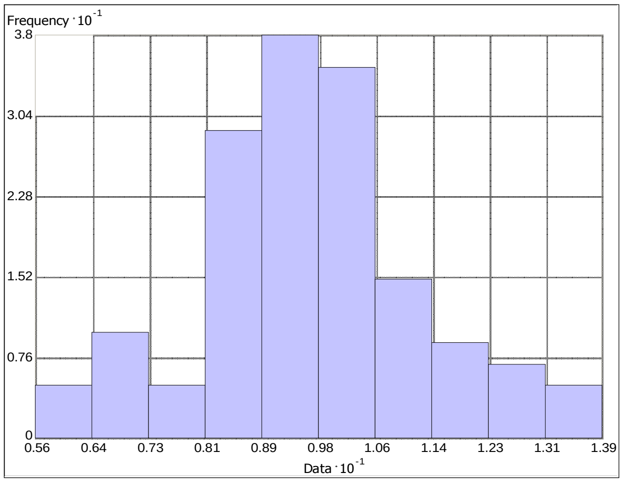
Study Site 3 potential box turtle habitat.

	PATCH ID	TYPE	AREA (ha)	PERIM (m)	SHAPE INDEX	CORE (ha)	PROX
1977	129	Agriculture	22.1	4,674.0	2.5	0.1	9,955.5
	436	Agriculture	20	3,534.0	2	0.3	1,616.1
	588	Agriculture	0.3	292.0	1.3	0.3	3,243.7
	138	Agriculture	18.4	5,566.0	3.2	1.7	6,148.3
	399	Agriculture	9.1	3,136.0	2.6	2.6	1,093.4
	99	Agriculture	17.4	4,968.0	3	5.1	6,508.0
	613	Agriculture	12.5	2,376.0	1.7	12.5	1,621.1
	223	Forest	0.1	192.0	1.7	0.1	1,065.6
	623	Forest	0.1	264.0	1.8	0.1	2,127.4
	221	Forest	0.1	158.0	1.5	0.1	4,874.3
	201	Forest	0.8	824.0	2.3	0.1	6,266.3
	57	Forest	73.1	9,628.0	2.8	0.2	36,553.9
	205	Forest	25.2	4,182.0	2.1	0.8	40,743.9
	189	Forest	3.3	2,726.0	3.7	2.5	16,157.0
	558	Forest	32.2	8,438.0	3.7	4.6	31,394.4
	193	Forest	71.5	10,026.0	3	6.3	22,847.4
	240	Forest	117.3	12,326.0	2.8	6.9	22,898.3
	2	Forest	150	14,328.0	2.9	18.7	1,318.4
	586	Forest	140.7	12,128.0	2.6	23	25,826.9
	194	Forest	72	7,114.0	2.1	25.4	22,012.5
	92	Forest	172	10,900.0	2.1	54.2	15,103.8
	44	Plantation	22.2	2,598.0	1.4	0.1	3,654.0
	177	TXlineROW	13.8	2,674.0	1.8	6.1	7,185.3
	174	TXlineROW	21.4	9,616.0	5.2	10.5	4,091.9
Total			1015.6	132,668.0		182.3	
1984	160	Agriculture	5.4	1,974.0	2.1	0.1	5,930.7
	153	Agriculture	21.3	4,390.0	2.4	0.1	8,169.6
	646	Agriculture	0.3	292.0	1.3	0.3	3,243.7
	484	Agriculture	20.3	2,980.0	1.7	1.2	1,685.3
	451	Agriculture	7.9	2,514.0	2.2	3.4	1,542.8
	118	Agriculture	16.6	4,836.0	3	4.8	6,268.7
	668	Agriculture	12.5	2,376.0	1.7	12.5	1,621.1
	248	Forest	0.1	192.0	1.7	0.1	1,014.0
	679	Forest	0.1	264.0	1.8	0.1	2,127.4
	67	Forest	5.1	1,754.0	1.9	0.1	2,813.5
	245	Forest	0.1	158.0	1.5	0.1	4,648.2
	224	Forest	0.8	824.0	2.3	0.1	6,034.5
	273	Forest	100.7	14,528.0	3.6	0.3	12,983.3
	83	Forest	7.7	1,728.0	1.6	0.7	5,066.3
	212	Forest	3.3	2,726.0	3.7	2.5	16,115.7
	608	Forest	32.2	8,438.0	3.7	4.6	31,267.0
	216	Forest	72.7	9,506.0	2.8	6.3	22,813.3
	2	Forest	47	9,010.0	3.3	7	26,349.5
	7	Forest	89.3	5,808.0	1.5	18.4	15,248.1
	644	Forest	140.3	12,352.0	2.6	23	25,231.6
	217	Forest	71.8	7,116.0	2.1	24.9	22,354.7
	110	Forest	152.3	8,788.0	1.8	57.7	8,928.1
	200	TXlineROW	13.8	2,674.0	1.8	6.1	7,185.3
	197	TXlineROW	21.4	9,616.0	5.2	10.5	4,140.0
Total			843.0	114,844.0		184.9	

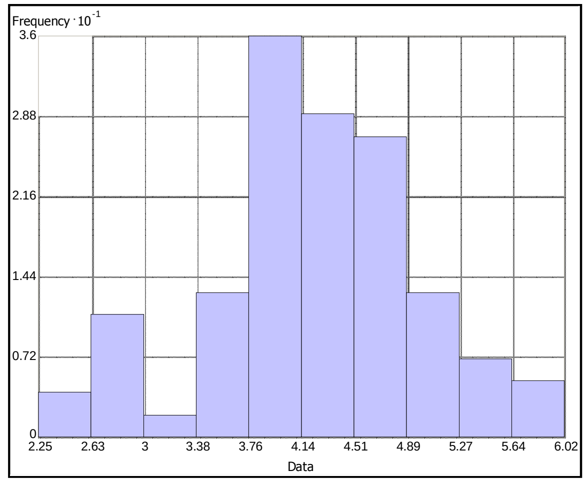
Continued. Study Site 3 potential Box turtle habitat.

	PATCH ID	TYPE	AREA (ha)	PERIM (m)	SHAPE INDEX	CORE (ha)	PROX
1997	777	Agriculture	0.3	292.0	1.3	0.3	2,650.8
	549	Agriculture	7.9	2,514.0	2.2	1.7	1,521.6
	139	Agriculture	17.7	4,514.0	2.7	4.8	6,826.4
	800	Agriculture	12.5	2,372.0	1.7	12.5	1,322.8
	296	Forest	0.1	158.0	1.5	0.1	4,646.6
	304	Forest	0.1	192.0	1.7	0.1	1,011.9
	81	Forest	3.8	1,400.0	1.8	0.1	2,648.7
	261	Forest	0.8	824.0	2.3	0.1	5,983.0
	817	Forest	0.1	264.0	1.8	0.1	2,127.1
	136	Forest	10.8	1,650.0	1.3	0.8	8,048.4
	2	Forest	44.2	9,084.0	3.4	1.6	23,155.9
	249	Forest	3.3	2,726.0	3.7	2.5	12,509.1
	774	Forest	122.9	16,516.0	3.7	3.0	16,344.2
	733	Forest	37.9	12,048.0	4.9	4.6	5,300.5
	8	Forest	78.7	7,242.0	2.0	10.6	13,517.1
	148	Plantation	28.7	3,474.0	1.6	11.6	4,368.2
	141	Plantation	63.7	3,996.0	1.3	54.2	1,994.8
	234	TXlineROW	21.4	9,616.0	5.2	2.8	4,140.0
	237	TXlineROW	13.8	2,674.0	1.8	6.1	7,185.3
Total			468.7	81,556.0		117.7	
2007	113	Agriculture	22.9	6352	3.3	3.7	7287.5
	775	Forest	0.1	264	1.8	0.1	2118.3
	2	Forest	42.1	10004	3.9	1.6	20050.0
	9	Forest	68.2	7290	2.2	2.2	12799.3
	256	Forest	3.3	2726	3.7	2.5	11078.9
	728	Forest	122.0	16532	3.7	2.8	16045.0
	689	Forest	34.6	9810	4.2	4.6	4331.9
	158	Plantation	18.9	4692	2.7	5.0	1316.4
	242	TXlineROW	21.4	9616	5.2	2.3	4864.6
	245	TXlineROW	16.3	2726	1.7	4.7	7497.0
Total			349.8	70,012.0		29.5	

Appendix F



Data Source: site 1_1963 Attribute: area_log



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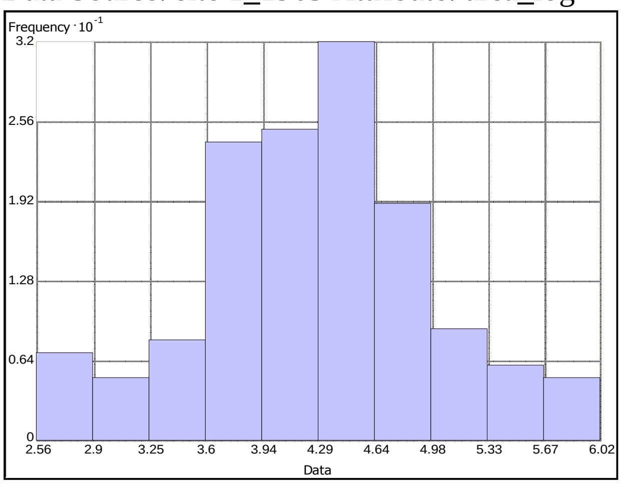
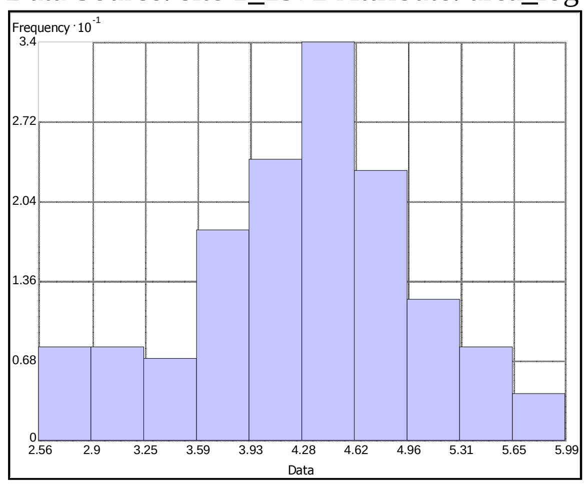


Data Source: site 1_1980 Attribute: area_log



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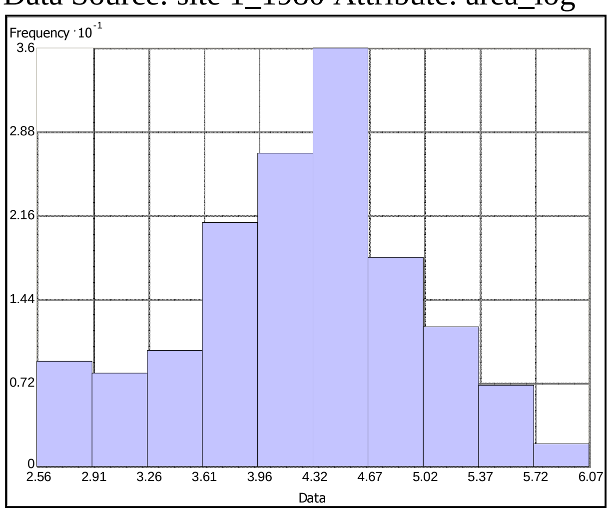
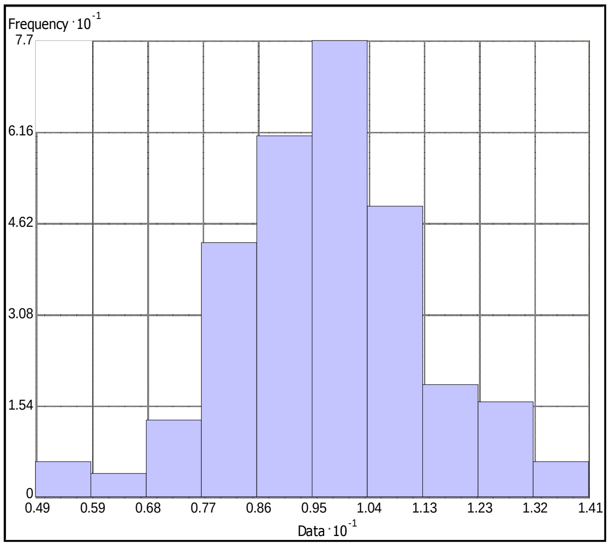
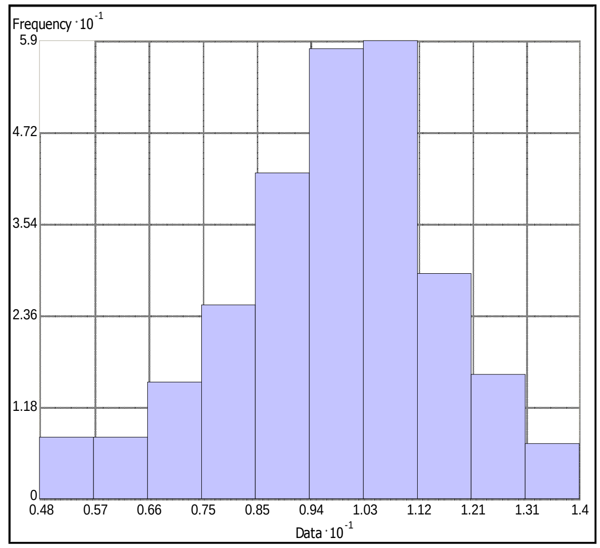


Data Source: site 1_2007 Attribute: area_log

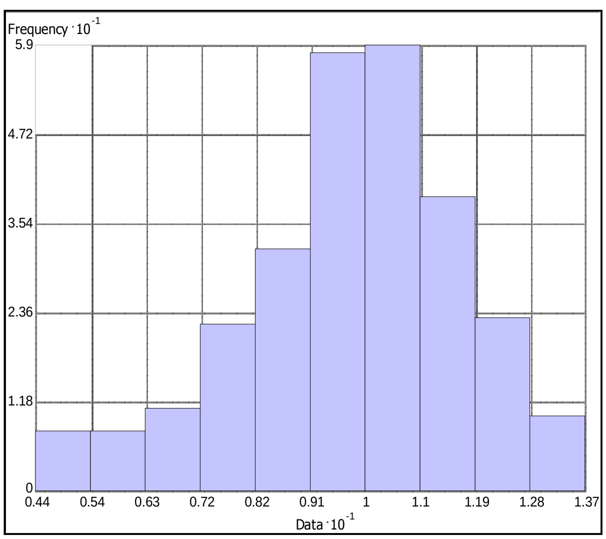
Figure F-1. Site 1. Histograms of variable area_log.



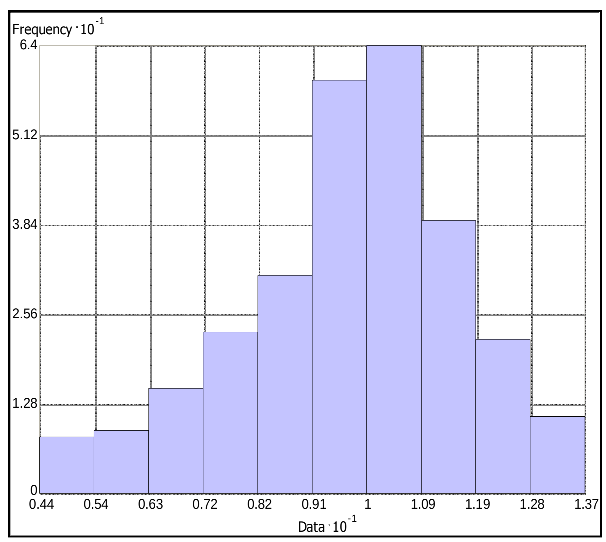
Data Source: site2_1963 Attribute: area_log



Data Source: site2_1985 Attribute: area_log

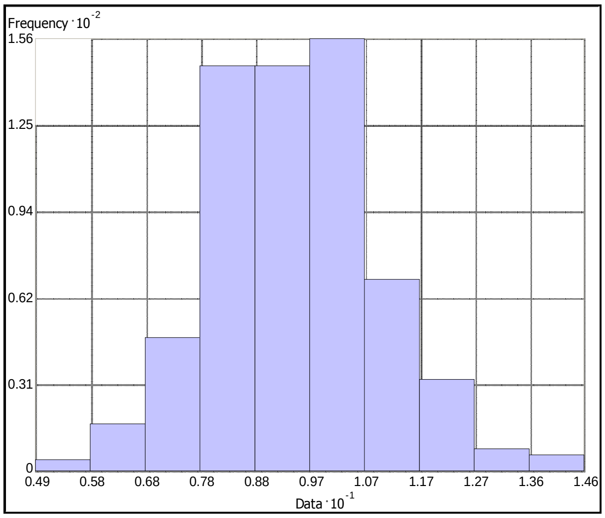


Data Source: site2_1997 Attribute: area_log

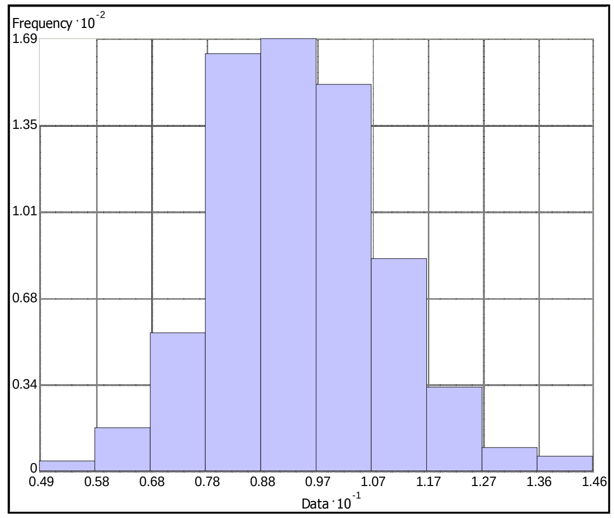


Data Source: site2_2007 Attribute: area_log

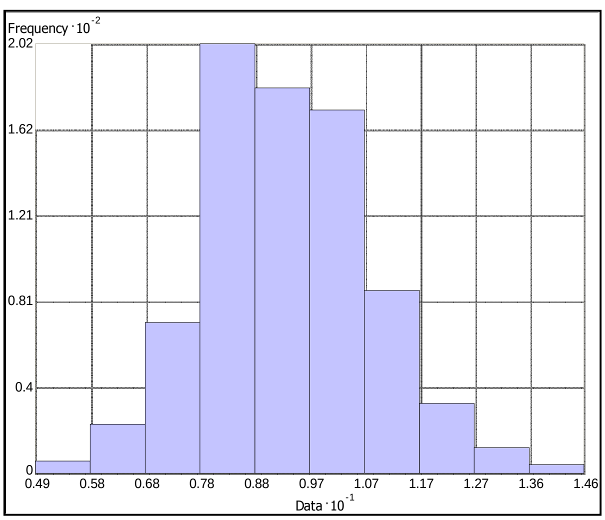
Figure F-2. Site 2. Histograms of variable area_log.



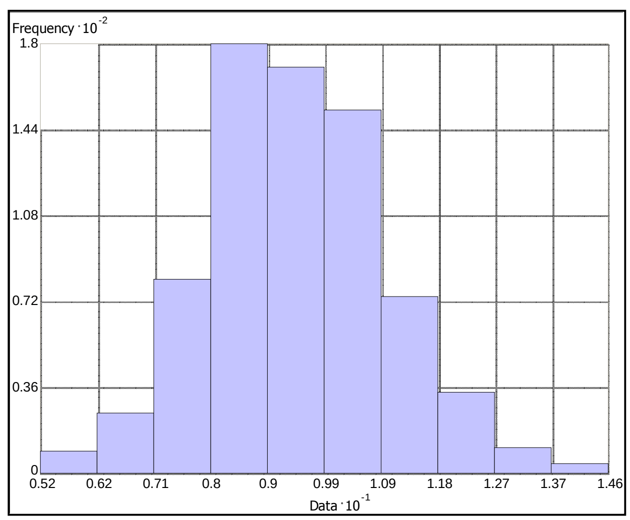
Data Source: site3_1977 Attribute: area_log



Data Source: site3_1984 Attribute: area_log

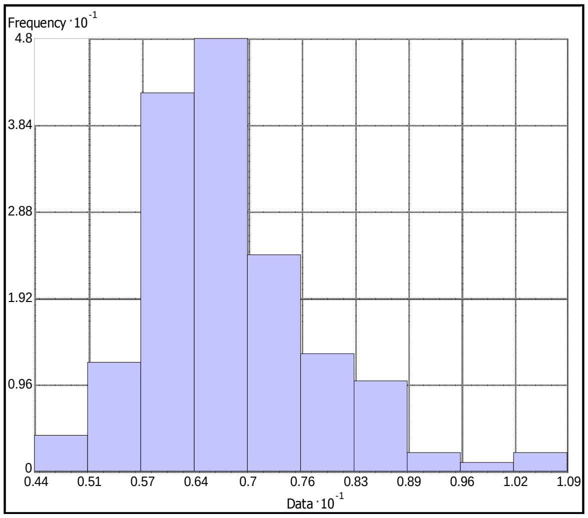


Data Source: site3_1997 Attribute: area_log

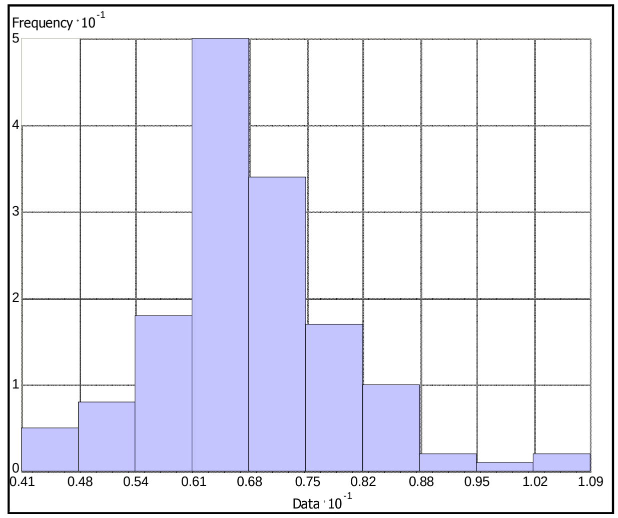


Data Source: site3_2007 Attribute: area_log

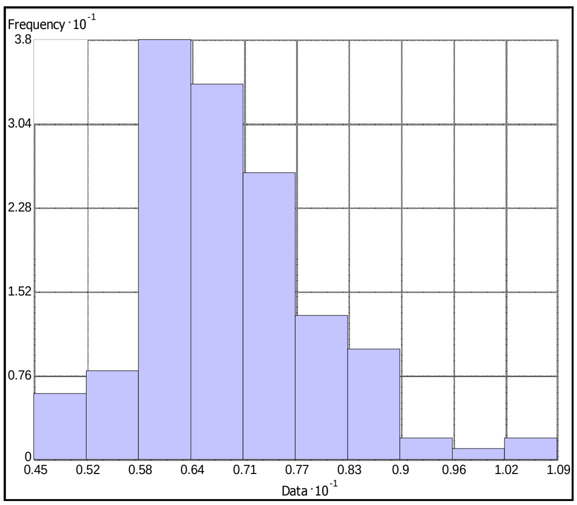
Figure F-3. Site 3. Histograms of variable area_log.



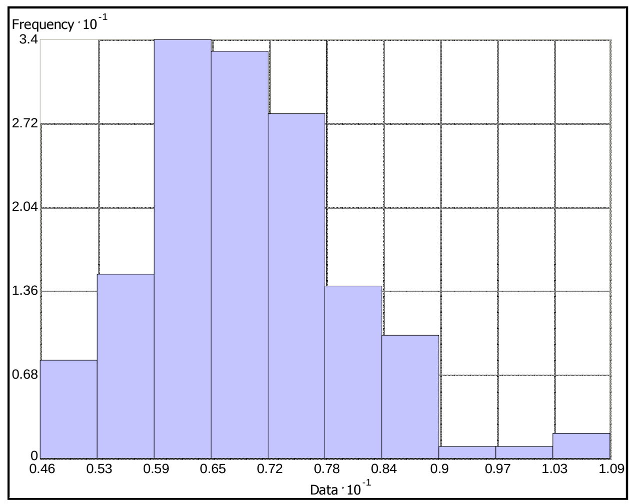
Data Source: site1_1963 Attribute:perim_log



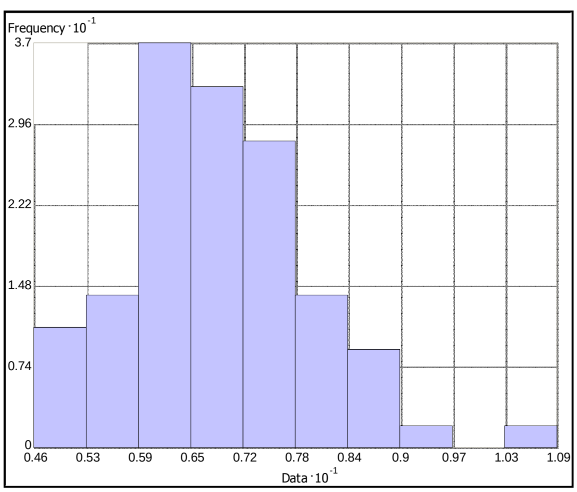
Data Source: site1_1972 Attribute: perim_log



Data Source: site1_1980 Attribute:perim_log

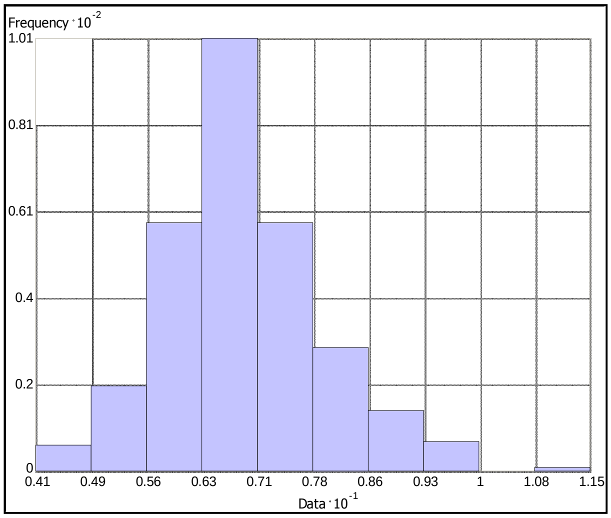


Data Source: site1_1997 Attribute: perim_log

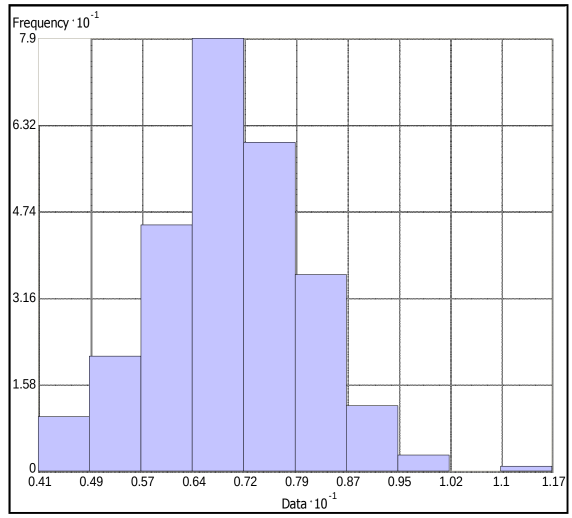


Data Source: site1_2007 Attribute:perim_log

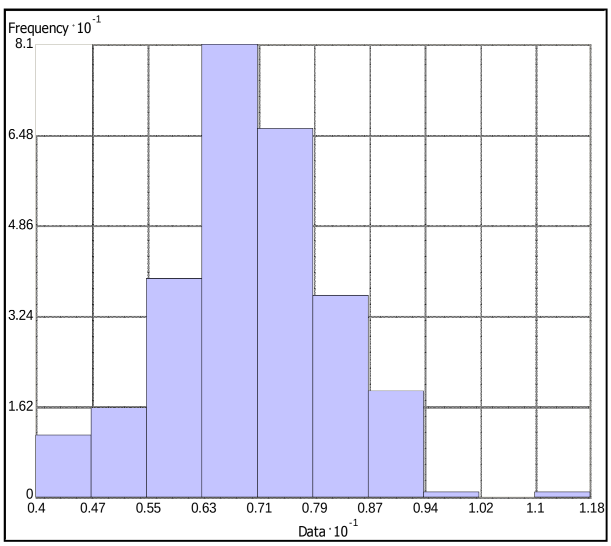
Figure F-4. Site 1. Histograms of variable perim_log.



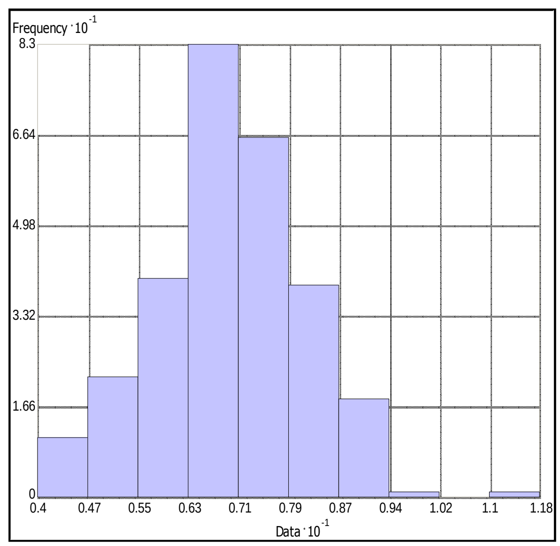
Data Source: site2_1963 Attribute: perim_log



Data Source: site2_1985 Attribute: perim _log

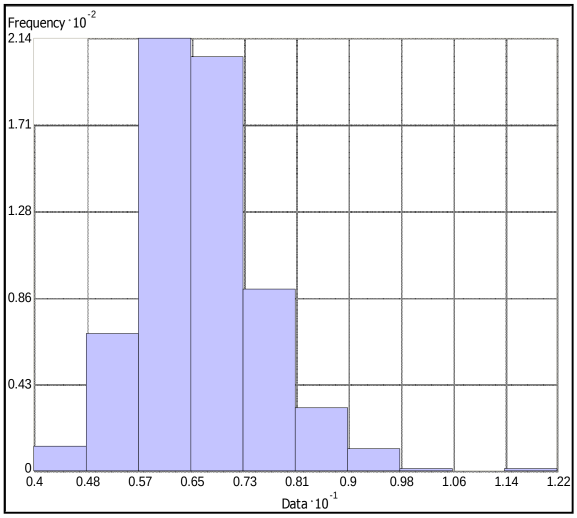


Data Source: site2_1997 Attribute: perim _log

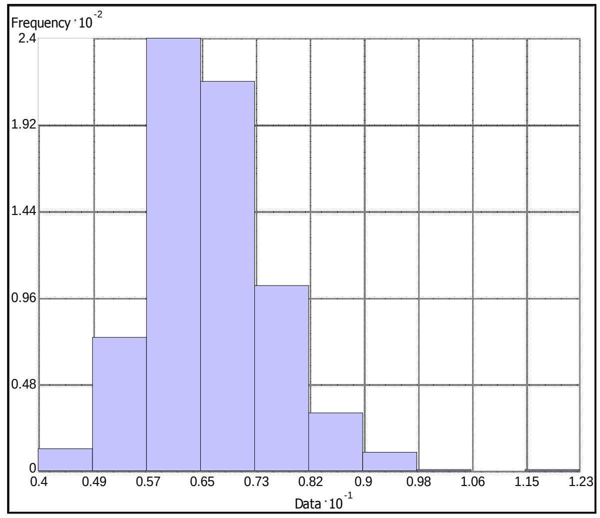


Data Source: site2_2007 Attribute: perim _log

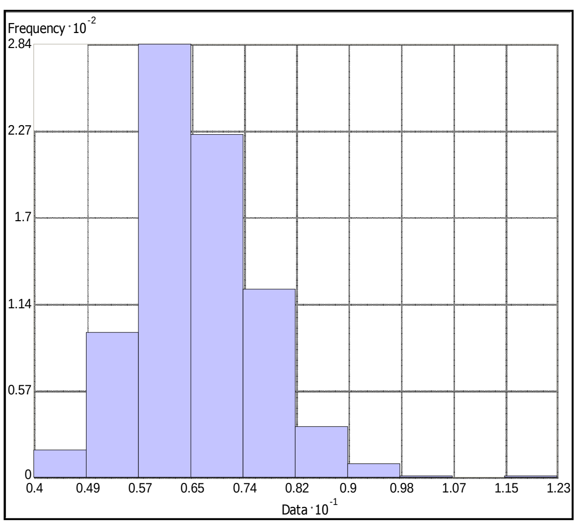
Figure F-5. Site 2. Histograms of variable perim_log.



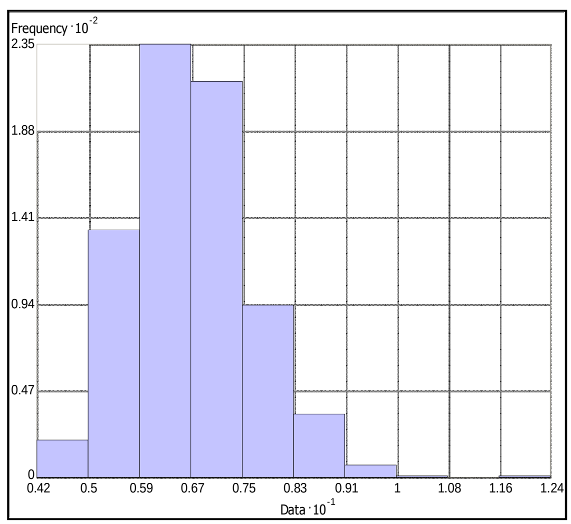
Data Source: site3_1977 Attribute: perim_log



Data Source: site3_1984 Attribute: perim_log



Data Source: site3_1997 Attribute: perim_log



Data Source: site3_2007 Attribute: perim_log

Figure F-6. Site 3. Histograms of variable perim_log.

Appendix G

Historic Land Loss

This region has a long history of land use conversion for human development. Prior to the construction of the Chickamauga Dam in 1941, the Tennessee Valley Authority (TVA) extensively studied the Tennessee River basin documenting that the previous widespread destruction of the forest by settlements was apparent by the stream interference from unprotected, eroding soils, which would reduce hydro-electric possibilities (Hudson et al. 1939). The building of Chickamauga reservoir diverted North Chickamauga Creek downstream from the dam, relocated the town of Soddy (The Chickamauga Project 1942) and flooded thousands of acres of farm land in Hamilton County (Rural Families of the Chickamauga Reservoir Area 1937).

During the late 1930s in Hamilton County, it was common practice to have 108 acre farms half in corn and hay and half in woodland (Rural Families of the Chickamauga Reservoir Area 1937). In 2002, the average size farm was 91 acres (USDA 2002). Most of the land use conversions from farming are to housing developments (RPA Comp. Plan 2006); between 2001 and 2005 half of the new major subdivision recordings in Hamilton County were in unincorporated areas (Chattanooga - Hamilton County Regional Planning Agency Development Trends). Between 1990 and 2000 Hamilton County population has increased 8% (Chattanooga-Hamilton County Regional Planning Agency (RPA) Comprehensive Plan 2030) but the county is reflecting a nationwide trend of decline of urban population and growing development in rural and forested areas. Cho et al. (2009) found that the amenity value of forested real estate increased during the 1990s in the Southern Appalachian Highlands.

Appendix H

Posey Point is in the state owned Cumberland Trail State Park and near where the trailhead is located. Since late 2006, this area has been actively strip mined for mountain stone, a popular type of sandstone exclusively found on the Cumberland Plateau. In February 2007, this area of the trail was closed because it was destroyed by strip miners (Chattanooga Times Free Press, Thursday, February 15, 2007). As of summer 2008, the state, who own the land but not the mineral rights, filed an injunction to prevent mining within 25 feet of the trail. The Free Press article goes on to quote the harvesters who say they will “smooth out the land, sow grass and replant trees when they are done”. The mineral rights owner argues that the state is trying to “take” the mineral rights from him. The Chattanooga Times Frees Press said in their Thursday, June 19, 2008 issue that the case is being decided by the Tennessee Appeals Court and the outcome will affect 11 Cumberland Plateau Counties.

Appendix I

The average market value (per acre) of a farm in Hamilton County

1987	$1,577
1992	$1,761
1997	$2,752
2002	$3,074

Source: USDA National Agricultural Statistics Service – 1992 & 2002 Census of Agriculture – County Data

Vita

Marie Colson was born in Birmingham, Alabama on September 25, 1949. She lived in Birmingham until she was twelve years old, then moved to Atlanta, Georgia, where she graduated from Towers High School in 1967. She moved to San Francisco, California in 1970 and pursued a career as a paralegal for 15 years. Marie moved to Chattanooga in 1985 and graduated from the University of Tennessee in Chattanooga (UTC) in 1995 and received a B.A. with a major in Environmental Science. In Marie's senior year at UTC she started working at TVA in the Geographic Information and Engineering Department and after graduation she became a full time employee at TVA, thus launching her present career as a Photo Interpretation Analyst. Marie has been a member of the American Society of Photogrammetry and Remote Sensing since 1998 (ASPRS) and has been a member of the Tennessee Geographic Information Council (TNGIC) since 2002.